Universität Hamburg
DER FORSCHUNG | DER LEHRE | DER BILDUNG

Exploring the potential for adaptation and mitigation to climate change of coffee agroforestry systems in Central America

Dissertation

with the aim of achieving a doctoral degree

at the Faculty of Mathematics, Informatics and Natural Sciences

Department of Earth Sciences

at Universität Hamburg

Submitted by

Leonel Demócrito Lara Estrada

From MANAGUA, NICARAGUA

HAMBURG, GERMANY | 2019

Accepted as Dissertation at the Department of Earth Sciences

Day of oral defense:	03.04.2019
Reviewers:	Prof. Dr. Uwe A. Schneider
	Dr. Livia Rasche
Chair of the Subject Doctoral Committee:	Prof. Dr. Dirk Gajewski
Dean of Faculty of MIN:	Prof. Dr. Heinrich Graener

Try and leave this world a little better than you found it, and when your turn comes to die, you can die happy in feeling that at any rate, you have not wasted your time but have done your best.

By Robert Baden-Powell

CONTENT

DEDICATION

to my mom, wife and children.

SUMMARY

Reaching a sustainable coffee production under frequent threats or limitations is a major concern for farmers and other actors in the coffee sector. Climate change effects are going to intensify progressively over time, and actions to adapt coffee systems need to be implemented. Given the complex interactions that occur in coffee agroforestry systems [CAFS] in Central America between coffee plants, trees and inputs, adaptation actions imply adjustments in the farming practices, which in turn influence the tradeoffs and synergies between productivity, adaptation, and mitigation to climate change. Knowing the potential of current coffee systems may help to define and promote the best farming strategies for the future, considering potential threats as well as the objectives of farmers for their plantations.

The primary objective of this thesis was therefore to define what the potential synergies and tradeoffs between productivity, adaptation and mitigation of CAFS in Central America are under climate change. Answering this question required two preliminary studies, one to identify what the impacts of climate change are on the coffee areas in the region, and one to examine what the potential of shading as an adaptation practices is. The Bayesian Network [BN] framework was selected as the main modeling environment, as it can use different sources of information, such as expert knowledge or data, summarize complex systems and deal with uncertainty.

First, a land evaluation was conducted for the Central American region; this included the creation of a new BN model "Agroecological Land Evaluation for *Coffea arabica* L." [ALECA] and the inference of the land suitability under current and climate change conditions. The results indicate that the current coffee areas will suffer a drastic reduction in their land suitability: About half of the areas currently classified as excellent and very good areas for coffee will become of moderate and marginal suitability for coffee by 2050 under the less severe climate change scenarios. This land suitability downgrade will likely decrease the quantity and quality of the coffee produced in the region.

Second, considering the adaptation potential of the cooling effect of shade trees in coffee agroforestry systems, a new simple BN model was created to infer the required shade level of coffee plantations based on air temperature. Suitability functions from ALECA were integrated into the shade model to estimate the air temperature suitability under shaded and unshaded conditions. The use of shade in the coffee plantations of Nicaragua was discussed and compared with inferred shade values to test and validate the model. Then, the required shade level and the corresponding effect on air temperature suitability in 2000 and 2050 [RCP 4.5] was inferred for the coffee areas in Nicaragua. A general increment in the shade levels is required, even in areas

where shading is currently not necessary, and the number of coffee areas that require high shade levels [≥ 60%] will double from 2000 to 2050. At lower altitudes, the cooling effect of shading may not be enough to alleviate the future warming conditions.

Third, there are efforts to promote agricultural systems oriented to adapt to and mitigate climate change. Hence, a new BN model was developed to identify the most promising farming strategies used in different farm types for coffee farming under climate change. For this, first a new farm typology system was created to capture and depict the potential for productivity, adaptation, and mitigation [PAM] synergies in CAFS. Five PAM-typologies were identified, differing in their shade levels, input intensities, and dominant tree types. In general, the farm type dominated by woody are located at low and medium altitude, used medium to high shade levels, and has higher synergies for productivity, adaptation and mitigation objectives; and the type dominated by musaceas are located at medium to high altitudes, used low to medium shading and has high synergy potentials for productivity and adaptation.

In a second step, a new BN model was used to identify the most promising PAM-typologies in 2000 and 2050 [RCP 4.5]. As objectives, a higher net income was set for productivity and a higher carbon content of the system for mitigation. The required shade levels obtained from the shade model were included as adaptation measures. The modeling targeted only productivity and adaptation for 2000; and productivity, adaptation, and mitigation for 2050. The PAM-typologies characterized by low to medium shade levels and high farming intensification were recommended for 2000, and medium to high shade levels and medium intensification for 2050. The recommended higher shade levels to alleviate the warming conditions in 2050 produced an increment about 50% in the carbon content of the CAFS and a reduction of less than 10% of the net income. In addition to the main coffee modeling studies, a BN model was developed to infer missing climate variables based on proxy variables, as missing data is a common situation in the land planning process, especially in developing countries. Relative humidity was used as the missing variable and air temperature, precipitation, solar radiation and wind as proxies.

This thesis shows that even under a relatively optimistic climate change scenario, the coffee areas in Central America will suffer a downgrade in the land suitability for cultivation of *Coffea arabica* L. An adaptation of shade levels will help to alleviate the warming conditions. A new farm typology of CAFS and a new model for productivity-adaptation-mitigation synergies are introduced to improve the analysis and evaluation of farming practices and strategies considering multiple objectives. If productivity, adaptation, and mitigation objectives are included in the farming strategy, an increase in the shade level and carbon content and a decrease in net incomes is observed. Only different shade levels and an intensification of management were considered.

To further improve the performance of CAFS under future conditions, more and new adaptation practices or strategies need to be tested in further studies.

ZUSAMMENFASSUNG

Die Erreichung einer nachhaltigen Kaffeeproduktion unter Bedrohungen wie dem Klimawandel oder Einschränkungen ist für Landwirte und andere Akteure im Kaffeesektor ein großes Anliegen. Die Auswirkungen des Klimawandels werden sich im Laufe der Zeit allmählich verstärken, und es müssen Maßnahmen zur Anpassung der Kaffeeanbausysteme ergriffen werden. Die komplexen Wechselwirkungen, die in den Kaffee-Agroforstsystemen in Mittelamerika zwischen Kaffeepflanzen, Bäumen und Betriebsmitteln bestehen, erfordern komplexe Anpassungen in den Anbaumethoden, die wiederum die Tradeoffs und Synergien zwischen Produktivität, Anpassung und Klimaschutz beeinflussen. Die Kenntnis des Potenziale der derzeitigen Kaffeeanbausysteme kann dazu beitragen, die besten Anbaustrategien für die Zukunft zu definieren und zu fördern, wobei sowohl potenzielle Gefahren als auch die Ziele der Landwirte für ihre Flächen berücksichtigt werden.

Das vorrangige Ziel dieser Arbeit war es daher, zu definieren, welches die potenziellen Synergien und Tradeoffs zwischen Produktivität, Anpassung an den Klimawandel und Klimaschutz von Kaffee-Agroforstsystemen in Mittelamerika sind; sowohl unter heutigen als auch zukünftigen klimatischen Bedingungen. Die Beantwortung dieser Frage erforderte zwei Vorstudien, eine, um die Auswirkungen des Klimawandels auf die Kaffeegebiete in der Region zu ermitteln, und eine zweite, um zu untersuchen, welches Potenzial die Beschattung als Anpassungspraktik hat. Als Instrument wurden „Bayesian Networks“ [BN] gewählt, welche verschiedene Informationsquellen wie Expertenwissen oder Daten nutzen, komplexe Systeme zusammenfassen und mit Unsicherheiten umgehen können.

Zunächst wurde eine Landbewertung für die mittelamerikanische Region durchgeführt, wofür ein neues BN-Modell "Agroecological Land Evaluation for Coffea arabica L." [ALECA] entwickelt und anschließend die Landeignung für den Kaffeeanbau unter aktuellen und zukünftigen klimatischen Bedingungen modelliert wurde. Die Ergebnisse deuten darauf hin, dass sich die Fläche, auf der zurzeit Kaffee angebaut wird, drastisch verringern wird: Etwa die Hälfte der derzeit als exzellent und sehr gut eingestuften Fläche für Kaffee wird bis 2050 unter den milderen Klimawandelszenarien nur noch von moderater und geringer Eignung für Kaffee sein. Diese Herabstufung der Landeignung wird die Quantität und Qualität des in der Region erzeugten Kaffees wahrscheinlich verringern.

In einem zweiten Schritt wurde ein weiteres BN-Modell entwickelt, welches die kühlende Wirkung von Schattenbäumen in Kaffee-Agrarforstsystemen berücksichtigt, um einen der Lufttemperatur angemessene Beschattungsgrad zu ermitteln. Auf diese Weise können die

Kaffeeflächen besser an neue klimatische Bedingungen angepasst werden. Hierfür wurden einige der Landeignungsfunktionen aus ALECA in das Schattenmodell integriert. Um das Modell zu testen und zu validieren, wurde die Verwendung von Schatten in den Kaffeeplantagen Nicaraguas erläutert und mit den durch das Modell ermittelten Beschattungsgraden verglichen. Angewendet wurde das Modell dann, um die erforderlichen Beschattungsgrade aller Kaffeeflächen Nicaraguas sowohl im Jahr 2000 als auch 2050 [RCP 4.5] zu berechnen. Eine generelle Erhöhung der Beschattungsgrade ist erforderlich, auch auf Flächen, die derzeit keine Beschattung benötigen. Das Ausmaß der Flächen, die eine hohe Beschattung erfordern [≥60%], wird sich bis zum Jahr 2050 verdoppeln, und in niedrigeren Höhenlagen reicht die kühlende Wirkung der Beschattung möglicherweise nicht aus, um die zukünftigen Erwärmungsbedingungen zu mildern.

Es bestehen Bemühungen, Agrarsysteme zu fördern, die auf die Anpassung an den Klimawandel und dessen Eindämmung ausgerichtet sind. Daher wurde im dritten Teil der Dissertation ein BN-Modell entwickelt, das die vielversprechendsten Anbaustrategien für verschiedene Kaffee-Agroforstsysteme unter sich wandelnden klimatischen Bedingungen identifizieren kann. Hierfür wurde zunächst ein neues Klassifizierungssystem für Kaffeeplantagen geschaffen, welches helfen soll, die Potenziale für Produktivität, Anpassung und Klimaschutz [PAM] der Flächen besser zu erfassen und darzustellen. Es wurden fünf PAM-Typologien identifiziert, die sich in ihren Beschattungsgraden, Betriebsmitteln und dominanten Baumarten unterscheiden. Im Allgemeinen befinden sich die von Gehölzen dominierten Kaffeeplantagen in niedriger und mittlerer Höhe, sie haben mittlere bis hohe Beschattungsgrade zeigen viele Synergien bei Produktivität, Anpassung und Klimaschutz. Die von Bananengewächsen dominierten Kaffeeplantagen befinden sich auf mittleren bis hohen Höhen, haben niedrige bis mittlere Beschattungsgrade und zeigen ebenfalls viele Synergiepotenziale bei Produktivität und Anpassung.

In einem zweiten Schritt wurde das BN-Modell verwendet, um die vielversprechendsten PAM-Typologien für die Jahre 2000 und 2050 zu identifizieren. Als Ziele wurden ein höheres Nettoeinkommen, das heißt eine Steigerung der Produktivität, und als Klimaschutzmaßnahme ein höherer Kohlenstoffgehalt des Systems festgelegt. Als Anpassungsmaßnahme wurden die aus dem Schattenmodell gewonnenen erforderlichen Beschattungsgrade einbezogen. Das Klimaschutzziel wurde nur für die Modellierung des Jahres 2050 verwendet. Für das Jahr 2000 eignen sich besonders diejenigen PAM-Typologien, welche sich durch niedrige bis mittlere Beschattungsgrade und ein hohes Maß landwirtschaftlicher Intensivierung auszeichnen. Für das Jahr 2050 hingegen eigenen sich PAM-Typologien mit mittleren bis hohen Beschattungsgraden und einer mittleren Intensivierung besser. Die empfohlenen höheren Beschattungsgrade im Jahr 2050 führen zu einem Anstieg des systemeigenen Kohlenstoffgehalts von 50% und zu einer Verringerung des Nettoeinkommens um 10%.

Um die Modellierung in den drei Hauptteilen der Dissertation zu unterstützen, wurde ein zusätzliches BN Modell entwickelt, welches fehlende Klimavariablen mittels Proxy-Variablen abschätzt, da besonders in Entwicklungsländern Datensätze oft Lücken aufweisen oder Daten gar nicht erhoben werden. Hier zum Beispiel wurde die relative Luftfeuchtigkeit anhand von Lufttemperatur, Niederschlag, Sonneneinstrahlung und Wind abgeschätzt.

Diese Arbeit zeigt, dass sich die Flächen, auf denen momentan in Mittelamerika Coffea arabica L. angebaut wird, in Zukunft nicht mehr so gut wie jetzt für den Kaffeeanbau eignen werden, selbst unter einem relativ optimistischen Klimaszenario. Um die Auswirkungen des Klimawandels abzumildern, können die Beschattungsgrade angepasst werden, da hierdurch die Temperaturen in den Kaffeeplantagen leicht sinken. Zur besseren Erfassung der Synergien und Tradeoffs zwischen dieser Anpassungsmaßnahme und Produktivität und Klimaschutz wurde ein neues Klassifizierungssystem für Kaffeeplantagen geschaffen. Wenn sowohl Produktivitäts-, als auch Anpassungs- und Klimaschutzziele in die Anbaustrategie einbezogen werden, kann eine Erhöhung des Beschattungsgrades und des Kohlenstoffgehalts sowie ein Rückgang des Nettoeinkommens beobachtet werden. In dieser Arbeit wurden nur unterschiedliche Beschattungsgrade und eine Intensivierung des Managements berücksichtigt. Um die Leistung von Kaffee-Agroforstsystemen unter zukünftigen klimatischen Bedingungen weiter zu verbessern, müssen mehr und neue Anpassungspraktiken oder -strategien in weiteren Studien getestet werden.

List of Figures

List of Tables

1. INTRODUCTION

Agricultural systems are diverse in complexity and purpose. Such diversity is the result of the interaction between land conditions and human decisions in rural areas (McConnell and Dillon, 1997; Miller and Gross, 2011; Thrall et al., 2010). The current state of coffee production systems in Central America have been shaped by a series of consecutive decisions made by farmers to deal with natural, economic and political factors at different periods in time (Charlip, 1999; Kaimowitz, 1996; Samper, 1999). Ideally, the planning and decision process begins even before the plantations are established, when farmers or agronomists or both evaluate the qualities of the land for coffee production (FAO, 1993; Somarriba, 2009). The land evaluation considers the state of agronomical factors such climate, soil, and landforms as well as other non-agronomical factors like land ownership, accessibility or existing infrastructure (FAO, 1976; Hopkins, 2014; McRae and Burnham, 1981). Subsequently, the degrees of optimality of the land suitability factors are examined, the limitations assessed and possible farming practices to overcome such limitations defined and evaluated. Finally, the farmer's individual preference, expertise, experience, assets, and risk aversion are considered to define their ultimate farming strategy (Somarriba, 2009). If the land suitability or the farmer's objectives change, or new opportunities or crises appear, the farming strategy should be adapted.

In the last decades, several crises and extreme events have negatively impacted the coffee sector in Central America, such as recurrent low coffee prices, rising production costs, coffee rust epidemics, land use changes, armed conflicts and wars, and lack of proper government policies (Avelino et al., 2015a; Blackman et al., 2006; CEPAL, 2002; Charlip, 1999; FAO, 2001; Kaimowitz, 1996; Pérez, 2001; Samper, 1999). Climate change is the next big challenge for the region (Gay et al., 2006; Haggar and Schepp, 2012), in some cases even exacerbating current problems like coffee rust epidemics (Alves et al., 2011). In order to rise to the challenge, the magnitude of the possible impacts of climate change on the coffee sector needs to be appraised, and adaptation strategies planned. Such information plays a vital role in the decision-making process to define the most suitable farming strategies at the local level and to formulate adaptation policies at the national level. This is a challenge, however, as the coffee systems in the region are very diverse, and tools for aiding in the decision-making not readily available.

In Central America, most of the coffee is cultivated under the shade of trees in agroforestry systems [CAF]. CAFs provide multiple benefits and advantages to farmers and ecosystems such as stabilizing the coffee production, income diversification by providing more than one good, provision of food and shelter to wild species, reduction of erosion, and enhancement of the soil and microclimatic conditions in the coffee plantation (Barradas and Fanjul, 1986; Beer, 1987; Blanco and Aguilar, 2015; Lin and Lin, 2010; Moguel and Toledo, 1999; Perfecto et al., 1996). The regulation of the microclimate is one of the most promising services of agroforestry, as it can serve as an adaptation strategy. Compared to full-sun conditions, shading reduces the temperature and maintains the humidity in the coffee plantation (Lin, 2010). CAFS also have a high mitigation potential compared to unshaded crop systems due to the perennial nature of trees and coffee plants, which provides a standing stock of carbon and a source of organic matter to the soil carbon compartment (Ehrenbergerová et al., 2015; Segura et al., 2006). Finding the correct level of shade is a delicate matter, however, as variations in shade require changes in the number of trees, and provoke changes in coffee yields and the dynamics of weeds, pests, and diseases (Aguilar et al., 2003; Haggar et al., 2011; MacVean, 1997; Mariño et al., 2016). These interactions can be depicted as synergies and tradeoffs (Harvey et al., 2014). Exploring the synergies and tradeoffs between productivity, adaptation, and mitigation in the existing CAFS may help to identify the most promising CAFS for future farm planning and help with policy-making in the region.

However, in comparison to coffee grown in monoculture, coffee agroforestry systems are more difficult to model because of their vertical, horizontal and temporal complexity (Roupsard et al., 2009; Somarriba et al., 2004). The available process-based models for CAFS have many parameters, are highly data-demanding and are either limited to plot level analyses or the study of particular interactions between components of CAFS (Luedeling et al., 2016; Rodríguez et al., 2011; Van Noordwijk and Lusiana, 1998; van Oijen et al., 2010). Given the technical limitations in purely process-based modeling, innovative modeling frameworks are needed that capture and model CAFS in such manner that allows their application and usability in decision-making processes (Luedeling et al., 2016; Roupsard et al., 2009). A land suitability evaluation framework is such an option, as it is well suited to deal with the impacts of climate change on coffee production (Hood et al., 2006).

Land suitability evaluations for coffee have been conducted for countries in the Caribbean and African region. They integrated climate, soil and landform in a geographic information system framework under current conditions, but did not consider the uncertainty surrounding the input and output data (Mighty, 2015; Nzeyimana et al., 2014), uncertainty due to missing or incomplete data is a common situation in agricultural planning in those regions. Furthermore, some global studies have evaluated the impacts of climate change on coffee production considering only the climatic suitability for coffee (Bunn et al., 2014; Ovalle-Rivera et al., 2015). They used models based on the presence/absence data of wild species (Guillera-Arroita et al., 2014; Phillips et al., 2006; Yackulic et al., 2013), which raises some concerns, as cultivated coffee does not follow natural patterns of distribution. In conclusion, there is a lack of tools and information about current and future land suitability for cultivated coffee that also consider uncertainty and can be used as an aid in decision-making. Such tools and information need to be available to define strategies to tackle the impacts of climate change on coffee production in Central America.

Bayesian Networks [BNs] have been identified as suitable tools to depict environmental and decision making processes. BNs only require a few parameters and can be used to summarize complex systems, integrate different sources of information and knowledge, and deal with different sources of uncertainty. The graphical user interface with its explicit and interactive environment provides users like farmers, agronomists, or land managers the opportunity to easily understand the system and explore the implications of different management decisions (Aguilera et al., 2011; McCann et al., 2006; Uusitalo, 2007). More details on the advantages and disadvantage of BNs can be found in the different chapters of the thesis.

1.1. Outline of the dissertation

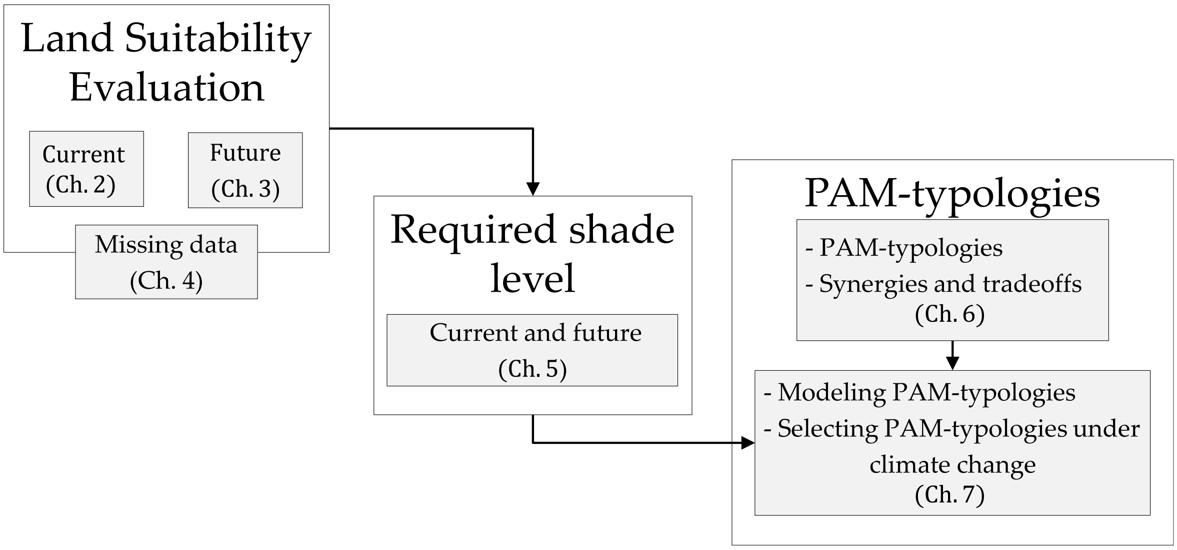
In this thesis, I introduce a new Bayesian Network framework to evaluate the land suitability for coffee production and the synergies and tradeoffs between productivity, adaptation and mitigation to climate change in coffee agroforestry systems. The building of the framework includes a series of steps where new tools and data are generated in an integrated manner.

In Chapter 2, a new BN model is introduced and used to evaluate the land suitability for coffee production under current conditions in Central America. The land suitability is estimated based on climate, soil and landform data. Different types of data uncertainty are discussed and evaluated. In Chapter 3, the expected land suitability under climate change is estimated for the region using climate data projections based on RCPs 2.6, 4.5 and 8.5 for 2050 and 2080. As an option to deal with missing data in land evaluations, I provide a methodology to infer missing climate variables from proxy variables in Chapter 4. The chapters provide novel tools and a valuable source of information for the coffee sector in Central America.

In Chapter 5, a new simple BN model of shade levels in CAFs is introduced and used to estimate the required shade levels and the impact on the air temperature suitability for coffee cultivation in different regions of Nicaragua. The section includes a comparison between observed and modeled shade values and a discussion about the usage of shading by farmers. Then, the required shade levels under a scenario of climate change are estimated for the coffee areas in Nicaragua. To the best of my knowledge, this is the first time that this kind of analysis has been done for the region.

In Chapter 6, I describe the creation of a new farm typology to better explore the tradeoffs and synergies between productivity, adaptation and mitigation objectives in coffee agroforestry systems. In Chapter 7, a new BN model is presented that identifies the most suitable farm typology for each coffee area in Nicaragua under climate change by determining the type with the highest productivity and mitigation potential.

The following figure summarizes the research framework conducted in this thesis by chapters:



2. MODELING LAND SUITABILITY FOR *Coffea arabica* L. IN CENTRAL AMERICA[1]

2.1. Introduction

The agricultural sector faces the challenge of producing enough goods for a growing population. This challenge is exacerbated by changes in climate and the depletion of soil and water, factors that determine the suitability of land for agricultural production (Godfray et al., 2010). Information about the spatiotemporal variations of these factors is necessary for efficient agricultural planning processes at the farm, local and regional scales. Agricultural planning involves the inventory and classification of available resources to define the biophysical potential of land for crop production, called land suitability evaluation. Most land suitability evaluation systems assess climatic, soil and landform factors, while others also include anthropogenic factors such as local production systems, relevant cultural customs, policies, others (Littleboy et al., 1996; McRae and Burnham, 1981; Verheye, 1987).

Commonly, land suitability evaluation systems are used at national or regional scales to generate spatial representations of land suitability for different crops or animal production systems. However, they can also be used at local or farm level by farmers and other stakeholders themselves. The advantage, in this case, is that a more accurate evaluation can be performed due to the availability of more detailed farm data, but often the expertise required to operate the models is lacking (Jakeman et al., 2006). Another drawback is that the majority of land suitability evaluation systems provide limited options to deal with uncertainty, which is a common feature in land evaluation processes, and environmental modeling in general (Refsgaard et al., 2007). Bayesian networks offer a solution to this problem: BNs can manage uncertainty (of data and knowledge), integrate expert knowledge, and combine qualitative and quantitative information. Bayesian networks can also integrate complex systems from different domains and aggregate model dimensions to the level required, making them a suitable tool for ecological modeling and land suitability evaluations (Aguilera et al., 2011; Chen and Pollino, 2012; Poppenborg and Koellner, 2014).

[1] Lara-Estrada, L., Rasche, L., Schneider, U.A., 2017. Modeling land suitability for *Coffea arabica* L. in Central America. Environmental Modelling & Software 95, 196–209.
https://doi.org/10.1016/j.envsoft.2017.06.028

Land suitability evaluation systems are especially relevant for managing risks in cropping systems with perennials, as the initial investments are higher, there is a waiting period of 3-4 years before the first harvest can be brought in, and resources are tied up for more extended periods. One such example is coffee (*Coffea arabica* L.). Many smallholder farmers' livelihood in coffee producing countries depends on its cultivation. Its production is reliant on a number of biophysical factors, such as climate, soil, landform, genetics and farming practices, whose relevance varies from site to site (Bertrand et al., 2011; Haggar et al., 2011; Silva et al., 2013; Wang et al., 2015). In recent years, coffee producers have experienced a series of income losses due to market failures, pests and diseases, the depletion of resources, extreme weather events, and a changing climate (Avelino et al., 2015a; Tucker et al., 2010; Vega et al., 2003).

In light of the recent shocks and changing biophysical factors, it is desirable to develop mechanisms to describe and quantify the impacts of these changes on land suitability for coffee production. Some authors used species distribution models to explore the climatic suitability for coffee at regional and worldwide levels (Bunn et al., 2015, 2014; Chemura et al., 2015; Ovalle-Rivera et al., 2015). These models use coffee maps as presence data together with climate information to predict climatic suitability for coffee production. This approach assumes that climate is the only explanatory variable of coffee presence in a given location, and farmers' actions to improve biophysical conditions or the influences of legal and socioeconomic factors are mostly excluded. Others, like D'haeze et al. (2005), explored the soil suitability (under the same climate conditions) for Robusta coffee using the Automated Land Evaluation System software based on the Framework for Land Evaluation of FAO (1976). Both studies focus on only one aspect of the environment, yet the response of species to environmental conditions are better explained by combining soil, topographical and climatic variables. While soil and topography are broadly aligned to climate, in practice, different soil types, e.g. can be found under the same climatic conditions and vice versa (Coudun et al., 2006; Franklin and Miller, 2009). Mighty (2015) and Nzeyimana et al. (2014) thus used multi-criteria analyses including climate, soil and landform variables in geographical information systems to evaluate land suitability for coffee in Jamaica and Rwanda, respectively.

All of these studies either look at a variety of factors but exclude uncertainty, or include uncertainty in their assessment but focus only on either soil or climate as the determining factor for coffee suitability. To date, no land suitability evaluation system includes all relevant factors for coffee production as well as uncertainty and has the potential to be used by scientists as well as stakeholders in coffee production. We, therefore, present in this paper the first Bayesian network model for the Agroecological Land Evaluation for Coffea arabica L. (ALECA) in Central America.

2.2. Materials and Methods

2.2.1. Study area

The study area encompasses the region of Central America spanning latitudes from 7.21° to 18.4°N and longitudes from 92.21 to 77.16°W, covering the countries of Guatemala, Belize, El Salvador, Honduras, Nicaragua, Costa Rica and Panama (Figure 1)

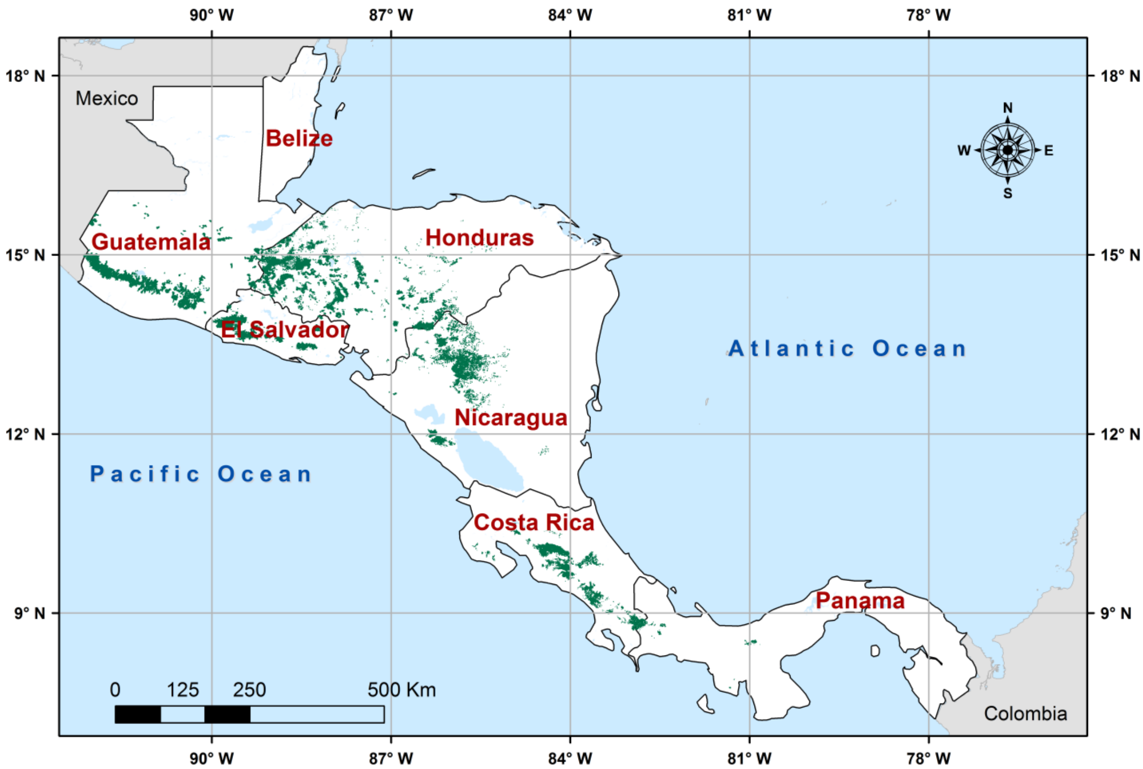


Figure 1. Study area in Central America. Coffee areas are marked green[2].

The area experiences tropical to subtropical conditions with a strong influence from the Atlantic Ocean. Dry winters and wet summers characterize the regional climate, whereby Atlantic regions experience more rainfall and higher humidity (>80%) than Pacific ones (Taylor and Alfaro, 2005). Average variations in mean air during the year are minimal (<4 °C) and decrease from North to South, but may be larger locally due to changes in topography (Magaña

---

[2] Guatemala: Ministerio de Agricultura y Ganadería, 2010. El Salvador: Ministerio de Agricultura y Ganadería, 2010. Honduras: Instituto Nacional de Conservación y Desarrollo Forestal, 2013. Nicaragua: Ministerio de Agricultura y Forestal, 2012. Costa Rica: Instituto del Café de Costa Rica, 2013. Panamá: Instituto Nacional de Estadísticas y Censo, 2012.

et al., 1999; Taylor and Alfaro, 2005). Due to the low variability in temperature, precipitation is the climatically more important determinant (Taylor and Alfaro, 2005). Even under future climate scenarios, where temperatures are expected to increase by 3 to 4 °C, the projected decrease in precipitation and increase in precipitation variability is regarded as the major threat to the region (Giorgi, 2006; Karmalkar et al., 2011).

Cultivation of *Coffea arabica* L. in Central America started in the 18th century in the Pacific region (Ukers, 1935). In some aspects, the cultivation systems differ little in the area (Samper, 1999); most of the coffee is cultivated in agroforestry systems, where trees are planted in coffee plantations to generate goods and services to the coffee plants and farmers (Somarriba et al., 2004), and 99% of coffee grown is Coffea arabica, with 1% *Coffea canephora* Pierre ex A. Froehner (Robusta) in Guatemala (USDA, 2015). Currently, nearly one million hectares are used for coffee production in Central America, generating 8 to 11% of the worldwide coffee supply (ICO, 2015).

2.2.2. Model development

2.2.2.1. Selection of variables

We started with a literature review to identify the key agroecological variables influencing coffee cultivation. Generally, coffee plants are sensitive to climate, soil conditions and farming practices (Camargo, 2010; Wang et al., 2015), in the literature described by the variables altitude, mean annual temperature, mean annual maximal temperature, annual mean precipitation, dry season length, relative humidity, wind speed, pH in H2O, cation exchange capacity, soil organic carbon content, bulk density, soil texture, slope and aspect (Alégre, 1959; Descroix and Snoeck, 2004; Silva et al., 2013). From this list, we excluded altitude for our model, which is typically used as a proxy to define optimal and suboptimal climatic conditions for coffee (Avelino et al., 2005; Vaast et al., 2008), but which is only a substitute for temperature, which we use directly, wind speed and relative humidity due to gaps in data and information about its influence on coffee suitability, mean annual maximum temperature due its high correlation to mean annual temperature (Pearson coefficient $r=0.96$ and $p<0.00001$), which we calculated for the region based on WorldClim data (Hijmans et al., 2005), and soil organic matter due to its only in- direct influence on coffee plants. With this variable selection, we are in line with other authors recommendations for agricultural land evaluation (McRae and Burnham, 1981; Sys et al., 1991) and coffee land evaluation (Descroix and Snoeck, 2004; Mighty, 2015; Nzeyimana et al., 2014).

For the selected factors, we compiled their optimal, suboptimal and unsuitable levels for coffee production (Table 1). Mean annual temperatures of 18 to 21°C are thought to be ideal for coffee production (Alégre 1959). Temperatures above this range hasten the ripening of the coffee berry flesh before complete bean maturity is reached and consequently, the coffee quality declines (Vaast et al., 2006). Also, plant growth is reduced, and vegetative abnormalities start to occur at too low or high temperature (Camargo, 1985 and Franco, 1958 cited by DaMatta and Ramalho, 2006).

Table 1. Agroecological variables selected to describe coffee land suitability in Central America with unsuitable, suboptimal and optimal values as reported in the literature.

Component	Variables	Unit	Unsuitable	Suboptimal	Optimal
Climate	Mean annual temperature	°C	≤10[1,2], ≥30[3,6], >32[2]	<15-16[3], <17-18[4] >23[3,4], >26[5]	18-21[3], 18-23[4]
	Annual precipitation	Mm	<1000[7]	<1300[8], >3000[7,9]	1550-2000[10], 1600-1800[3]
	Dry season length	# months ≤ 60 mm	>6[11]	<2[12], 5-6[11]	2-4[13],3-4[14]
Soil	pH in H20	-	<4[8], >8[8]	<5, >6.5	5.5-6.5[9], 5.2-6.2[14]
	Cation exchange capacity	Meq 100g^{-1}		<5[15]	>22[15, 16]
	Texture	Categorical	Sand (>30%), heavy clay (clay>70%)[12,13]		Loam, clay loam, clay
Landform	Slope	%	>50[9], >70[17]	>40[7]	0-40[7]
	Aspect	Cardinal directions			East[18]

[1] Larcher (1981), [2] Jaramillo and Guzmán (1984), [3] Alégre (1959), [4](1985) cited by DaMatta and Ramalho (2006), [5]Nunes et al. (1973) cited by DaMatta and Ramalho (2006), [6] DaMatta and Ramalho (2006), [7] ANACAFE(2006), [8] Willson (1985), [9] Descroix and Wintgens (2004), [10]Forestier (1969) cited by Willson (1985), [11] Descroix and Snoeck (2004), [12] Maestri and Barros (1977), [13] Haarer (1958), [14]Robinson 1964 cited by Willson (1985), [15] Molina and Melendez (2002), [16] Verheye (2002), [17] Blanco and Aguilar (2015), [18]Avelino et al. (2005).

For precipitation, Wallis (1963) estimated water requirements of 951 mm year^{-1}, in practice, as much as 1500 to 2000 mm are desirable. Precipitation higher than 2500 mm year^{-1} can lead to waterlogging, a boost in fungal diseases, premature berry droppings, and ineffective fertilizer applications, amongst others (ANACAFE, 2006; Willson, 1985). Concerning the distribution of precipitation over the year, a dry season of 3e4 months is ideal to stimulate the main flowering and harvesting season in Central America. In regions closer to the equator, like Colombia, two short dry periods occur in a year facilitating two harvesting seasons. Longer dry seasons can lead to flowering and fruit abortions, and quality and yield decline (Cannell, 1985; Willson, 1985), which is why coffee farmers identified precipitation (droughts and excessive rainfall) as the primary climatic concerns in the region, followed by temperature (Eakin et al., 2014; Tucker et al., 2010).

Soil texture affects multiple soil properties that influence soil fertility and crop productivity. Since coffee productivity is sensitive to nutrient and water supply, sandy and heavy clay soils are avoided for their limitations in water and nutrient holding capacity and drainage. The pH and cation exchange capacity are critical indicators of nutrient availability in the soil. Coffee plants prefer slight to medium acidic soils (5.0 to 6.2) with a high cation exchange capacity. Unlike soil texture, pH and cation exchange capacity can be modified by farming practices, such as chemical fertilization, the addition of organic matter, burnings, etc. (Descroix and Snoeck, 2004; Osman, 2013). Slope defines the vulnerability of a site to erosion and determines the potential for mechanization. Thus, flat or low slopes are optimal, as steep slopes require major soil conservation practices and reduce the efficiency of farming practices (Descroix and Snoeck, 2004; Ramírez, 2009). The aspect influences temperature variations at microclimate level; in northern latitudes, south-facing slopes receive more sunlight that north-facing ones (Adams, 2010; Bonan, 2008) and Avelino et al. (2005) found that coffee cultivated on east-facing slopes produced a better coffee quality in two locations in Costa Rica. Philpott et al. (2008) discovered significantly higher landslides in southwestern-facing slopes during a hurricane in Mexico.

2.2.2.2. Suitability functions

We created suitability functions, i.e. response curves, for the selected variables based on the agroecological requirements of coffee, and the literature listed in Table 1. We used two kinds of functions: tables for discrete variables (texture and aspect) and equations for continuous variables. To create the equations, we firstly defined the suitability scores for the variable values based on literature, secondly graphed the suitability scores for each variable and finally identified the functions that best fit to each graph (Figure 2). In the case of tabular suitability functions, for soil texture, we defined the suitability scores from literature. For aspect, we used a survey of 600 coffee farms in Nicaragua (Nitlapan, 2012) to define the suitability of each cardinal direction by using an analysis of covariance, a mean separation test, and a weighted mean.

In the case of wild species, these types of functions describe the relationship of a species' occurrence in relation to values of an environmental condition (Austin, 1980; Franklin and Miller, 2009). In our study, the suitability functions describe how suitable the value of a variable is for coffee production considering coffee's ecology and agronomy aspects, ranging from 0 to 100% (Figure 2 and Table 2. Suitability functions of the selected agroecological variables. Suitability scores range from 0 to 100%. The values in the texture table denote that there is a probability of

99% that 'Sand' e.g. only has a suitability of 0 to 25% for coffee production, and a 1% probability that it is in the range of 25 to 50%.

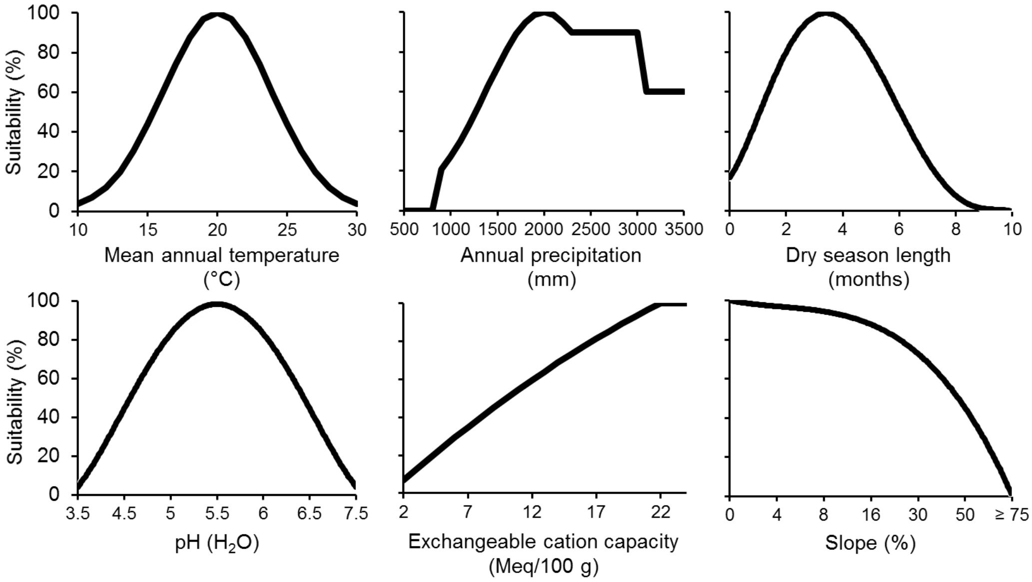


Figure 2. Graphical display of the suitability functions for continuous variables.

Table 2. Suitability functions of the selected agroecological variables. Suitability scores range from 0 to 100%. The values in the texture table denote that there is a probability of 99% that 'Sand' e.g. only has a suitability of 0 to 25% for coffee production, and a 1% probability that it is in the range of 25 to 50%.

<table>
<tr><th>Variables</th><th>Equations</th></tr>
<tr><td>Mean annual temperature</td><td>$S_{ti} = T_i \sim N(\mu,\sigma^2) \div T_\mu \sim (\mu,\sigma^2) \cdot 100$
Where S_{ti} is the suitability score for a given annual mean temperature in °C (T_i) and is distributed normally with mean $\mu = T_\mu = 20$ and variance $\sigma^2 = 3.89$</td></tr>
<tr><td>Annual precipitation</td><td>$S_{pi} = \begin{cases} 0, & if\ P_i < 800; \\ P_i \sim N(\mu,\sigma^2) \div P_\mu \sim (\mu,\sigma^2) \cdot 100, & if\ P_i < 2300; \\ 90, & if\ P_i \leq 3000; \\ 60, & Otherwise \end{cases}$
Where S_{pi} is the suitability score for a given annual precipitation in mm (P_i) and is distributed normally with mean $\mu = P_\mu = 2000$ and $\sigma^2 = 620.48$</td></tr>
<tr><td>Dry season length</td><td>$S_{di} = \begin{cases} 0, & if\ D_i > 8; \\ 0.252D_i^4 - 3.828D_i^3 + 14.149D_i^2 - 1.458D_i + 60, & Otherwise \end{cases}$
Where S_{di} is the suitability score for a given dry season length in months (D_i)</td></tr>
<tr><td>Slope</td><td>$S_{si} = 0.01\, S_i^2 - 2S_i + 100$
Where S_{si} is the suitability score for a given slope in percentage (S_i)</td></tr>
<tr><td>Aspect</td><td>$S_{ai} = \begin{cases} 80,\ if\ A = Flat; & 90,\ if\ A = West; \\ 72,\ if\ A = Southeast; & 93,\ if\ A = Southwest; \\ 80,\ if\ A = Northeast; & 97,\ if\ A = Northwest; \\ 80,\ if A = East; & 100,\ if\ A = South; \\ 87,\ if A = North; & \end{cases}$
Where S_{ai} is the suitability score for a given slope aspect (A)</td></tr>
<tr><td>pH (H_20)</td><td>$S_{pHi} = pH_i \sim N(\mu,\sigma^2) \div pH_\mu \sim (\mu,\sigma^2) \cdot 100$
Where S_{pHi} is the suitability score for a given pH (pH_i) and is distributed normally with mean $\mu = pH_\mu = 5.5$ and $\sigma^2 = 0.79$</td></tr>
<tr><td>Cation exchange capacity</td><td>$S_{ceci} = \begin{cases} 0, & if\ CEC_i < 1 \\ 100, & if\ CEC_i \geq 22 \\ -0.061CEC_i^2 + 6.114CEC_i - 5.053, & Otherwise \end{cases}$
Where S_{ceci} is the suitability score for a given cation exchange capacity in meq/100g (CEC_i)</td></tr>
<tr><td>Texture</td><td>$S_{ti} =$
<table>
<tr><th rowspan="2">Texture</th><th colspan="5">Suitability (%)</th></tr>
<tr><th>0 to 25</th><th>25 to 50</th><th>50 to 75</th><th>75 to 90</th><th>90 to 100</th></tr>
<tr><td>Sand</td><td>99</td><td>1</td><td>0</td><td>0</td><td>0</td></tr>
<tr><td>Sandy loam</td><td>99</td><td>1</td><td>0</td><td>0</td><td>0</td></tr>
<tr><td>Loamy sand</td><td>0</td><td>99</td><td>1</td><td>0</td><td>0</td></tr>
<tr><td>Loam</td><td>0</td><td>0</td><td>1</td><td>99</td><td>0</td></tr>
<tr><td>Silt loam</td><td>0</td><td>0</td><td>1</td><td>99</td><td>0</td></tr>
<tr><td>Silt</td><td>0</td><td>1</td><td>99</td><td>0</td><td>0</td></tr>
</table>
Where S_{ti} is the suitability score for a given soil texture (T_i)</td></tr>
</table>

2.2.2.3. Modeling in Bayesian Networks

Bayesian Networks are multivariate statistical models that comprise two main components: First, a directed acyclic graph composed of a set of random variables X = (X_1, [...], X_n) linked by arcs, where the arc direction defines direct dependencies between variables (parent and child nodes). Each variable has at least two mutually exclusive states. Second, a conditional probability distribution (conditional probability table) that quantifies the dependencies between variables. To illustrate, assume that X_1 is the child variable of parent variables X_2, […], X_n, written as P(X_1 ǀ X2, [...], X_n), which expresses the probability of X_1 occurring given the values of X_2, [...], X_n (Jensen and Nielsen, 2007b; Pearl, 1988). In our case, the combination of agroecological variables determines the level of suitability of a given piece of land for coffee cultivation. In a Bayesian network framework, this implies direct causal links be- tween each variable and the variable land suitability, i.e. p(Land Suitability ǀ variable_1, [...], variable_n). These multiple links create an exponential increment of model complexity due to the need to estimate the probability distributions for all possible combinations of the states of the agroecological variables (Landuyt et al., 2013). We avoided this complexity and at the same time increased the explanatory ability of the model by adding two intermediate levels (the S-variables and components) between each agroecological variable and the land suitability. This technique is known as *divorce* in graphical models and is commonly used to keep conditional probability tables tractable (Chen and Pollino, 2012; Jensen and Nielsen, 2007a). We built our model using the software Netica v.5.17 (Norsys Software Corp.).

The final graphical model (Figure 3) displays three evaluation levels: variables, components (groups of variables), and final land suitability (groups of components). The model scores and aggregates the suitability of the agroecological variables in each level to obtain the final land suitability, which we defined as the potential of a given unit of land to be used for viable coffee cultivation. In the first level, we created a node with discretized states for each variable and defined the maximum and minimum values of the variables (Pollino et al., 2007) and the priors from data available for the region (Figure 3) (Hengl et al., 2014; Hijmans et al., 2005). Then, we added a new child variable “S” to each agroecological variable and used the suitability functions to populate the conditional probability tables of the S-variables. In the second level, we grouped and aggregated the S-variables into the components climate, soil, and landform by using the Linear Combination Method (Hopkins, 2014). This method is a simple weighted sum of factors. We assigned the same weight to all S-variables. In the third level, we again used the weighted sum method to aggregate the components into the final variable Land Suitability, but this time assigned different weights to each component (49% to climate, 36% to soil and 15% to landform). The weights were calculated based on two coffee survey from Nicaragua (Lara-Estrada, 2005; Nitlapan, 2012) using Pearson's correlation coefficients between our selected variables and the coffee yields reported in the surveys.

After the structure of the model was determined, the priors of the agroecological variables were learned from data using the Counting-Learning Algorithm (Norsys, 2015) and the conditional probability tables of all child-nodes were populated using the described equations and weighted sums. Then the model was compiled and ready to use. An online version of the model is available at the following link:

https://www.hed.cc/?s=ALECA&t=ALECA

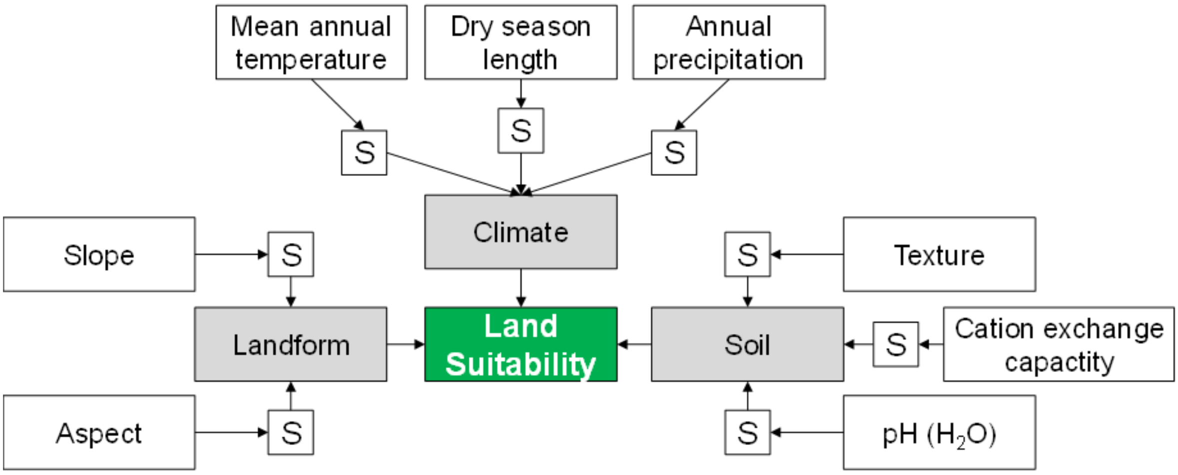


Figure 3. Graphical structure of the Agroecological Land Evaluation model for *Coffea arabica* L. (ALECA). Arrows indicate causal relationships between variables (from parent to child nodes). Level 1 (white boxes): suitability functions [0-100%] are used in the “S” nodes to evaluate the suitability levels of the agroecological variables for coffee cultivation. Level 2 (gray boxes): the suitability scores of Level 1 are aggregated into components. Level 3 (green box): the components are aggregated and weighted to obtain the final land suitability score. The units of the S variables, the components and the final land suitability score are percent.

Table 3. Description of the state values for the selected variables.

Variables	States*
Level 1	
Annual mean temperature [°C]	4-9.99, 10-11.99, [...], 26-27.99, 28-29.99
Annual precipitation [mm]	500-999.99, 1000-1249.99, [...], 2750-2999.99, 3000-6499.99
Dry season length [months]	0, 1, 2, 3, 4, 5, 6, 7, 8
Slope [%]	0-1.99, 2-3.99, [...], 16-29.99, 30-59.99, 60-99.99
Aspect [cardinal direction]	North, Northeast, East, Southeast, South, Southwest, West, Northwest, Flat
pH in H_20 [-]	2-2.49, 2.5-2.99, 3-3.49,[...], 7-7.49, 7.5-7.99
Cation exchange capacity [Meq 100 g^{-1}]	2.5-4.99, 5-7.49, [...], 17.5-19.99, 20-22.49, ≥22.5
Texture [categorical]	Sand, Loamy sand, Sandy loam, loam, Silt loam, Silt, Sandy clay loam, Clay loam, Silty clay loam, Sandy clay, Silty clay, Clay
S variables [%]: Annual mean temperature, Annual precipitation, Dry season length, Slope, pH in H_20, Cation exchange capacity	0-9.99, 10-19.99, [...], 80-89.99, 90-99.99
S variable Aspect [%]	70-79.99, 80-89.99, 90-99.99
S variable Texture [%]	0-24.99, 25-49.99, 50-74.99, 75-89.99, 90-99.99
Level 2	
Component suitability [%]: Climate, Landform and Soil	0-9.99, 10-19.99, [...], 70-79.99, 90-99.99
Level 3	
Land Suitability [%]	0-9.99, 10-19.99, [...], 70-79.99, 90-99.99

2.2.3. Data sources

For the simulations, we used the WorldClim dataset (Hijmans et al., 2005) to extract precipitation and temperature and calculate dry season length. WorldClim provides climate data in raster format from interpolated observations for the period 1950 to 2000 and also includes digital elevation [90 m aggregated at 1 km] from the Shuttle Radar Topography Mission (SRTM). We used this data to estimate the slopes and aspect [0 to 3600], which was converted to cardinal directions (ESRI, 2008). Sand, silt and clay content, cation exchange capacity and pH in H2O were downloaded from the SoilGrids portal (www.soilgrids.org). SoilGrids is a worldwide 3D spatial dataset for chemical and soil physical properties at 1 km resolution (Hengl et al., 2014). Soil data were available from 0 to 200 cm depth in layers of 5 cm; we used the average of the layers between 0 at 30 cm depth. Lastly, we merged all climate, landform and soil data into a single dataset, where each pixel [1 km resolution] corresponds to one "land case" to be evaluated in the model.

2.3. Sensitivity analysis

The influence of a parent variable on a child variable is defined by the prior distribution, the variable states (i.e. size and bounds) and the equations or conditional probability tables inside the child variable (Bennett et al., 2013). To explore the influence of the chosen agroecological variables on land suitability, we ran a sensitivity analysis using the variance reduction metric. The higher the variance reduction value of a variable is (scoring from 0 to 100%), the greater its influence on land suitability (Marcot et al., 2006; Norsys, 2015). We also examined the influence of the single components' scores on land suitability.

The analysis shows that the components climate and soil and their respective agroecological variables (except texture) influence land suitability most, and that results are not very sensitive to the landform component. Inside the components, mean temperature plays the most important role in the climate, pH in the soil and slope in the landform component (Figure 6). The low variance reduction of landform results a) from the low weight derived for the landform component, and b) from the narrow distribution of slope and aspect in our gridded input dataset, where, due to the resolution, extremes in slope, which would restrict or prohibit coffee cultivation on some plots, are filtered out. Since ALECA was also developed to be applied to specific plots on farms, this may not always be the case. Steep slopes facilitate soil erosion and hinder the efficiency of agronomic practices (Okoth et al., 2007; Tilman et al., 2002), which is why a flat or low slope is more desirable on a piece of land with excellent or good conditions of soil and climate (land suitability > 85%) than a steep slope and will be better ranked. For an explanation of how to the components' scores interact to define the final land suitability, see Figure A1.

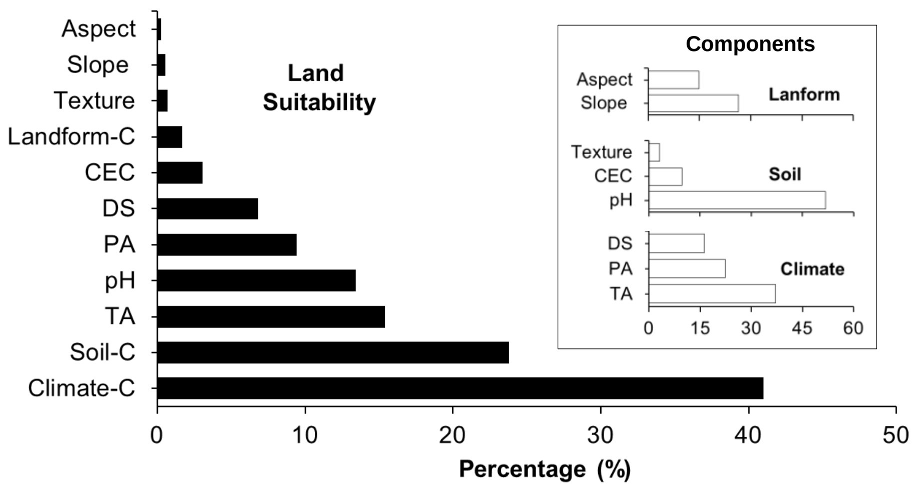


Figure 4. Sensitivity analysis of model results using variance reduction for land suitability (left) and components (right). CEC: cation exchange capacity, DS: dry season length, PA: mean annual precipitation, TA: mean annual temperature.

2.4. Model validation

Validating a model like ALECA is difficult due to the nature of its results, which do not give data on the presence/absence of coffee, but provide a score of 0-100% indicating the suitability of a specific land unit for coffee cultivation. We nevertheless decided to compare our model results with regional data of the spatial distribution of coffee areas (Figure 1), assuming that the distribution of current coffee areas is the result of a historical and technical selection for the best possible and available areas (Rueda and Lambin, 2013; Samper, 1999), and that consequently ALECA should score their land units high on the suitability scale. Some plantations may be located in areas of lower suitability since farming practices like the planting of shade trees improve land suitability by lowering temperatures (Haggar et al., 2011; Siles et al., 2010), but no coffee plantations should be located on completely unsuitable areas.

The results of this exercise show that there is indeed a close fit between patterns of coffee areas reported in national coffee maps and areas scored as suitable for coffee production by our model (Figure 5; maps of the entire region from Figure A2 to Figure A5). Areas with coffee plantations have a mean land suitability score of 85% (SD=5.34), nearly 98% of the plantations are located in areas with a suitability higher 70%, only 2% of the areas are ranked 60 to 70%, and no coffee plantations have land suitability scores below 60% (Figure 5).

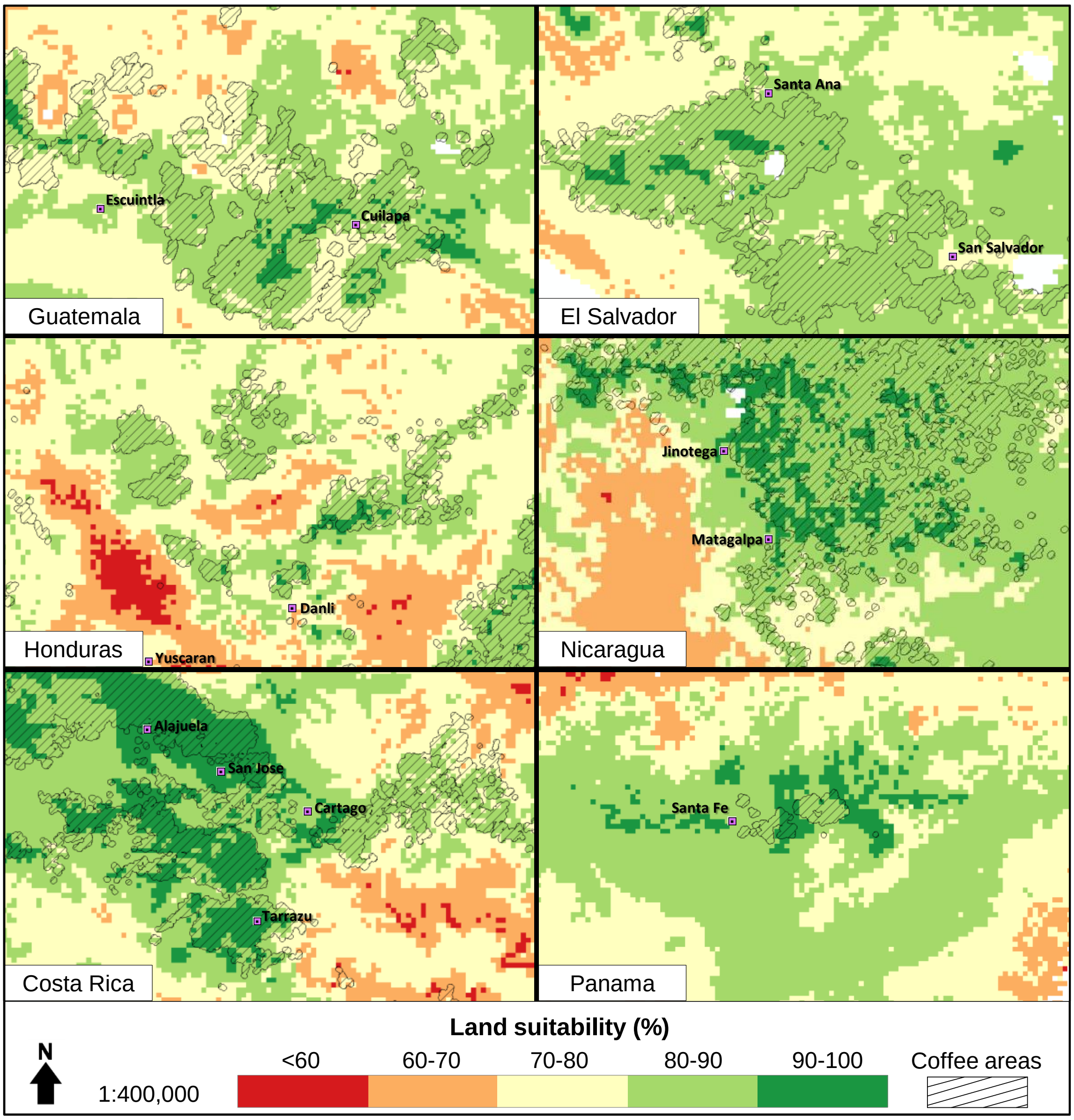


Figure 5. Map of reported coffee areas and simulated land suitability scores in selected areas of Central America. Coffee is usually grown in areas with a high estimated suitability, indicating a good model performance. Pixel size is 1 km.

Table 4. Simulated land suitability scores of current coffee and non-coffee areas for *Coffea arabica* L. in Central America with GUA=Guatemala, HON=Honduras, ESV=El Salvador, NIC=Nicaragua, CR=Costa Rica, PAN=Panamá. A graphical presentation of the data can be found in the supplementary material.

Land suitability score (%)	Coffee areas								Non-coffee areas	
	GUA	HON	ESV	NIC	CR	PAN	∑ %	∑ km²	%	km²
<60	<0.01	<0.01	-	-	<0.01	-	<0.01	<1	3.20	15,776
60 - 69	1.90	0.06	<0.01	0.09	0.06	-	2.11	224	17.34	85,469
70 - 79	18.25	2.62	0.96	1.56	0.99	0.30	24.68	2,614	44.75	220,678
80 - 89	14.99	17.33	11.88	11.15	3.66	0.46	59.47	6,302	32.75	161,489
90 - 100	2.08	2.99	1.82	2.49	4.26	0.10	13.74	1,456	1.96	9,677
Total	37.22	23.00	14.66	15.29	8.97	0.87	100	10,598	100	493,089

In comparison, non-coffee areas have a mean land suitability score of 76% (SD=7.70), with 80% located in areas with a suitability higher 70%, 17% in areas ranked 60 to 70%, and 3% in areas with suitability scores below 60%. We assume that the occurrence of coffee plantations in areas ranked 60 to 70% is the result of social and agronomical factors, such as planting coffee for land reclamation purposes (Charlip, 2003). Additionally, the use of farming practices like agroforestry systems and better adapted genetic material have permitted farmers to extend coffee production to sites with a lower suitability ranking (Lashermes et al., 2009; Lopez-Rodriguez et al., 2015; Muschler, 2001). Guatemala, for example, the country with the highest proportion (54%) of coffee areas rated between 60 and 80% suitability, is also the only country in Central America with a significant Robusta production (*Coffea canephora* Pierre ex A. Froehner). This coffee specie is better adapted to warmer conditions than *Coffea arabica* L. (USDA, 2015; Willson, 1985), indicating that the simulated lower suitability scores may be realistic. The relatively high proportion of non-coffee areas with scores higher 70% shows that there is a great expansion potential in Central America for coffee production. It should be kept in mind, however, that non-coffee areas include urban and protected areas, coasts, roads, and other land uses that are not immediately available for plantations. We conclude from this validation study that, taking local social and agronomical factors into account, ALECA performs well in terms of land suitability scoring of potential coffee areas.

In a second validation study, we compared the simulated land suitability scores of eight coffee reference zones with their conventionally reported suitability for coffee cultivation, hoping to show that ALECA simulates higher scores for prime coffee areas than for areas known to be of lesser suitability. The selected zones are located in Honduras, Nicaragua and Costa Rica and include the zones Marcala and El Paraíso in Honduras (Teuber, 2009), Jinotega, Masatepe and

Nueva Guinea in Nicaragua (Haggar et al., 2011; Vaast et al., 2004), and Tarrazú, Turrialba and San Carlos in Costa Rica (Muschler, 2001; Siles et al., 2010). According to the literature and commonly held views, the region Tarrazú is considered as optimal, Jinotega and Marcala as very good, and Turrialba, Masapete, El Paraíso, Nueva Guinea and San Carlos as suboptimal for coffee production (Haggar et al., 2011; Muschler, 2001; Rojas, 1989; Vaast et al., 2005).

We found that Tarrazú, the only region ranked optimal, was also the region simulated to have the highest mean land suitability- scores among the reference zones. The determining factors for the high score were mainly climate and soil conditions (Figure 6), which is line with the assessments of other authors for Tarrazú (Bornemisza and Segura, 1999; Chinchilla et al., 2011; Rojas, 1989). Next in the land suitability ranking were Jinotega and Marcala, both also known in reality for their overall good production levels and coffee quality (IICA, 2003; Teuber, 2009). Jinotega scored slightly worse in the soil compartment and Marcala in the climate compartment than Tarrazú. Turrialba, Masatepe, and El Paraíso received suitability scores of 80 to 89% due to several limitations in climate, soil, and landform, with Turrialba having a better climate, and Masatepe better soil and landform conditions (cf. Haggar et al., 2011). Finally, even though Nueva Guinea showed the best landform conditions, non-optimal values in mean temperature and soil chemical properties resulted in a land suitability score of 73%, only above of San Carlos.

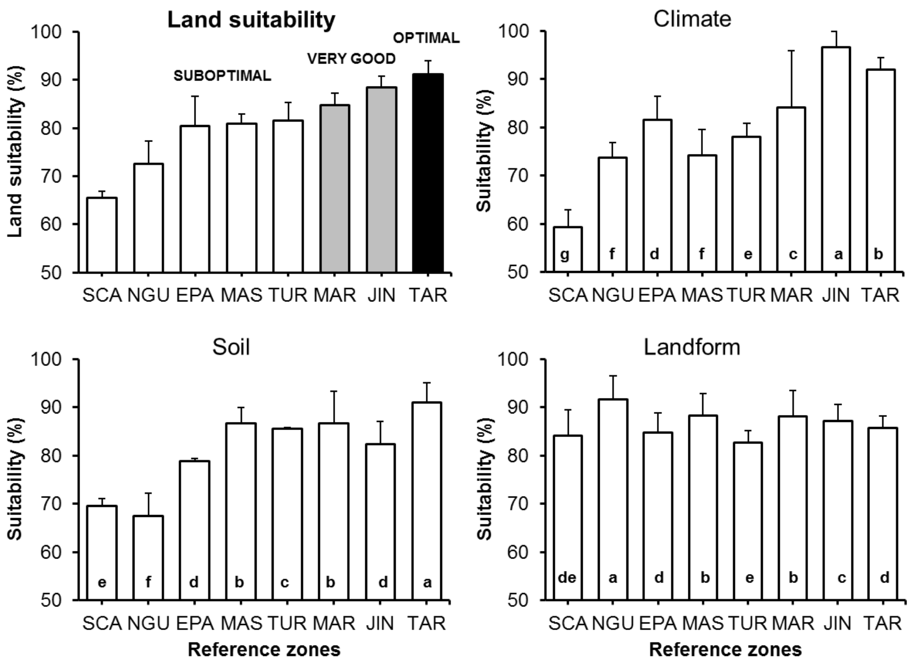


Figure 6. Overall land suitability and single component suitability scores of the coffee reference zones in Central America. In the land suitability figure, the colors black (optimal), grey (very good) and white (suboptimal) indicate the commonly accepted classifications of the reference zones. Honduras: EPA=El Paraíso, MAR=Marcala; Nicaragua: NGU=Nueva Guinea, MAS=Masatepe, JIN=Jinotega; Costa Rica: SCA=San Carlos, TUR=Turrialba, TAR=Tarrazú.

Errors bars represent the standard deviation of the mean. Different letters inside bars indicate significant difference between reference zones (ANOVA by Fischer test; $p<0.01$).

This analysis shows that ALECA is not only able to assign high suitability scores to actual coffee areas in Central America as shown in the previous validation study, but also to reproduce reported quality patterns between single coffee areas. Figure 6 also shows that looking at the different component suitability scores instead of only the final land suitability score can help to under- stand the reasons behind the final ranking and facilitate a better decision support.

Based on the results of this validation study, we propose that land suitability scores above 90% can be categorized as optimal (cf. Tarrazú), 90 to 85% as very good (cf. Marcala and Jinotega), 84 to 75% as moderate (cf. El Paraíso, Masatepe, Turrialba), 74 to 60% as subopti- mal (cf. San Carlos and Nueva Guinea) and values below 60% as unsuitable for coffee production.

2.5. Application example using uncertain information

One of the main motivations for developing ALECA was that the Bayesian network approach allows users to consider data uncertainty. Users may have precise information for some variables and incomplete information for others, or may simply want to consider the inherent uncertainty of some input data, like e.g. soil sampling deviations or errors in rainfall measurements. To demonstrate ALECA's ability to deal with this issue and still deliver reliable results, we conducted a simulation using input data with added un- certainty and compared the results to simulations without uncertainty in the input data. We assumed that farmers can easily measure slope, soil texture, and dry season length and thus have precise information (hard evidence) for these factors. For the remaining variables, we used Netica's Uncertain Value Format, which allows users to represent different types of data uncertainty by using Gaussian distributions, intervals, a set of (im)possibilities and others (Norsys, 2015). In this case, we used the Gaussian uncertain value format to calculate a mean and standard deviation for each case value based on the input data for each land case and the state values of each agroecological variable (Table 3). We then ran the model with both input datasets, thus estimating land suitability scores with and without uncertainty in the input data, and finally calculated for both result datasets in order to evaluate model performance the Bayesian metrics quadratic loss and spherical payoff, and the conventional metrics bias, RMSE, and Index of Agreement (Marcot, 2012; Willmott, 1981).

Results show that the mean land suitability-scores were approximately the same, with 76.13% and an SD=4.88 calculated from the input dataset with added uncertainty and 76.29% with an SD= 7.7 from the original dataset (Figure 7). The use of data with uncertainty generated a land suitability score distribution with shorter tails, however. This finding indicates that in areas with land suitability scores ranged 60 to 90%, ALECA's performance is quite accurate even under uncertainty, but that in regions with low(<60%) or high suitability scores (>90%) results differ by ca. 5% between data with and without uncertainty. This difference is negligible in our case, as the qualitative ranking of areas does not change with a difference of 5%: areas with suitability values below 60% are unsuitable for coffee production in any case, and areas with values above 90% will remain optimal or very good.

Overall, the study shows that in the suitability range most coffee areas are in Central America are found in, ALECA can deliver a reliable analysis even under uncertainty and can thus be used as a decision support tool even in situations where data is missing or uncertain.

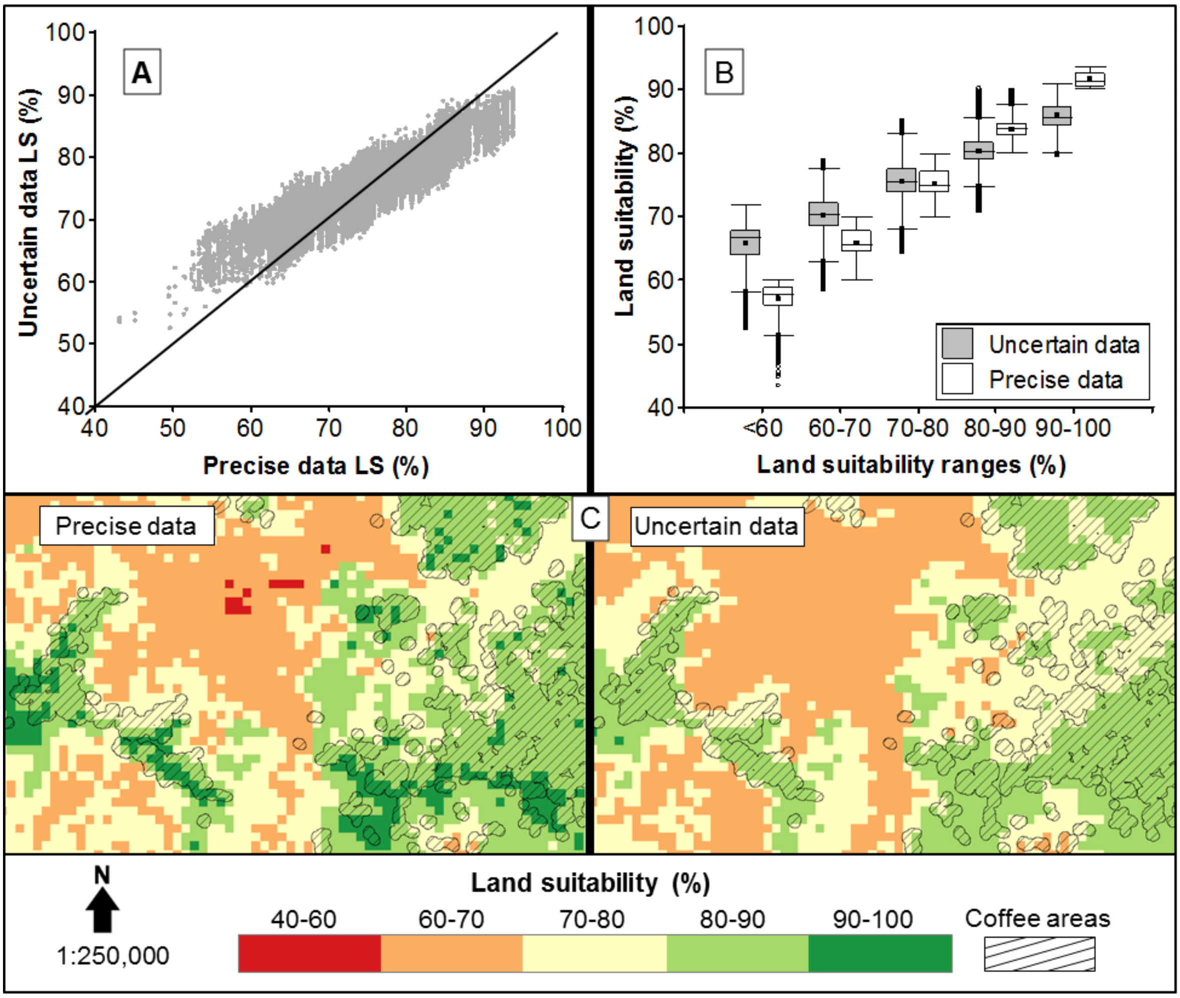


Figure 7. Land suitability (LS) scores simulated from input data with and without added uncertainty. A) Dispersion graph of LS scores. A bias (ca. 5%) is visible between datasets at low and high LS values. B) Box plot of the same values as shown in A). The classes on the x-axis only apply to the white boxes (input data without uncertainty). The grey boxes show the LS scores of the same land units, but with added uncertainty in the input data. C) Two maps of a randomly chosen coffee zone in Nicaragua.

2.6. Discussion

Bayesian networks are versatile tools for the creation of land suitability evaluation systems for coffee production. Unlike other land suitability evaluation systems (Bunn et al., 2014), models like ALECA have a transparent and informative graphical interface that allows users to evaluate the suitability of a given land unit for coffee cultivation at variable, component and aggregate level. Decision makers can see, explore and learn from the evaluation process (Jakeman et al., 2006; Ranatunga et al., 2008). Like Mighty (2015) and Nzeyimana et al. (2014), we used climate, soil and topography variables to define land suitability. The main difference between their variable selection and ours is that they used proxy variables like soil orders and geological information to represent the effect of soil properties in some cases, while we focused on variables with a direct influence on land suitability (Austin, 2002). Finally, the combined deterministic and probabilistic updating in ALECA allows the model to produce quick and accurate results by using i) deterministic updating when there is no uncertainty in the evidence for the parent variable(s) and no uncertainty in the equation or tables relating the child variable to its parent(s), and ii) probabilistic updating when uncertainty is present from any of those sources (B. Boerlage, Norsys Software Corp.; personal communication).

Some caveats should be kept in mind, however. First, we had to use data from different types of studies (surveys and trials), regions and conditions to develop the suitability functions, but assumed that the information appropriately represents the process under study (Rodríguez et al., 2011; van Oijen et al., 2010). Second, the literature largely refers to only *Coffea arabica* L. and ignores varietal differences (Bertrand et al., 2011; Lashermes et al., 2009). Thus, we also excluded varietal differences from our model. Third, there is uncertainty associated with the datasets we used that we did not consider in the validation procedure for the sake of clarity. We opted to demonstrate how this factor can be considered in the uncertainty exercise instead. Finally, like other land evaluation systems, ALECA uses a linear combination method to estimate land suitability, which is a weighted sum of individual variables' suitability that excludes any interactions and assumes variable independence (Hopkins, 2014). However, the influence of some variables can depend on the state of other variables. Medium to low amounts of annual precipitation, for example, have less of an impact on coffee when soil texture is clayey (Willson, 1985) and slope aspect modifies the temperature at the site level (Barry, 2008). Including these interactions would have required defining all conditional dependencies between the states of the different variables, which was not feasible due to lack of information. The model validation exercise showed that ALECA performs well even without considering these interactions, but we will nevertheless keep refining the model with any new data set that becomes available.

Plans for ALECA also include the addition of variables describing the impact of farming practices like mulching on soil properties and erosion reduction, irrigation on water supply and the planting of trees on microclimate and soil conditions. The shade of trees, for example, reduces the temperature under the canopy in agroforestry coffee plantations (Siles et al., 2010). By defining the potential of temperature reduction based on the level of shade, it is easily possible to explore changes in temperature suitability due to trees in ALECA. ALECA can also be adapted for use in coffee regions outside Central America by updating the bounds and priors of the variables to the new conditions. For the regions that experience lower annual or seasonal temperatures than Central America, the introduction of a variable like 'temperature of the coldest month' may be necessary (Woodward and Williams, 1987), but no further changes to the structure would likely be needed.

2.7. Conclusions

In this study, we introduce ALECA, the first Bayesian network model to evaluate land suitability for coffee production in Central America under uncertainty. The validation showed that even without the use of coffee maps as input, ALECA reliably scored the suitability of actual coffee areas for coffee production as higher than that non-coffee areas, and was able to accurately predict the known order of quality of several coffee reference zones in Central America. We further showed that the model can also be used as a reliable decision support tool for coffee stakeholders in situations where some input data is uncertain. The graphical structure of the model permits users to easily assess the main factors determining land suitability for coffee production, to explore how changes in these factors impact suitability, and to plan adaptation measures accordingly.

2.8. Appendices II

Appendix II-A. Influence of single components on final land suitability scoring

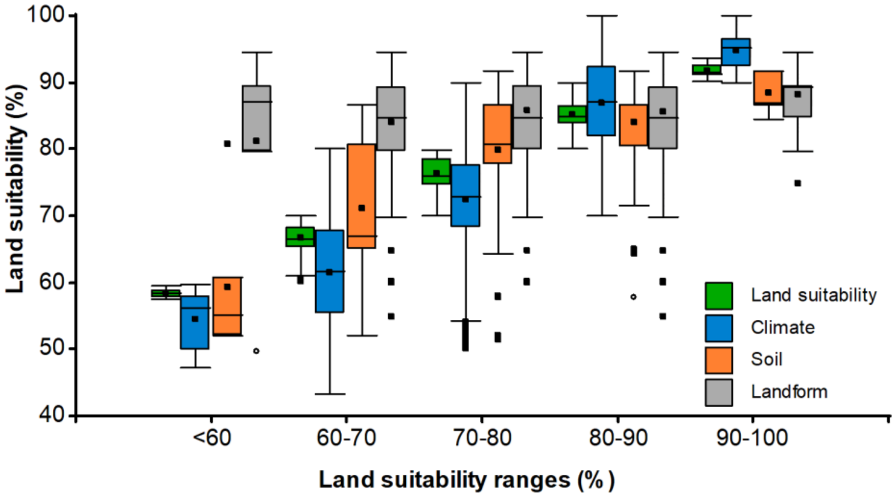


Figure A1. Suitability scores of single components and final land suitability score of coffee areas in Central America. The climate and soil components have a larger influence on the final land suitability score than landform. To achieve high or low land suitability scores, both climate and soil components need to have high or low values, indicating that no further analysis of causes is required. Intermediate land suitability values (60 to 80%) can arise from diverse component values, in which case the single component and variable values need to analyzed in order to identify the limiting factors for coffee production.

Appendix II-B. Suitability maps for *Coffea arabica* L.

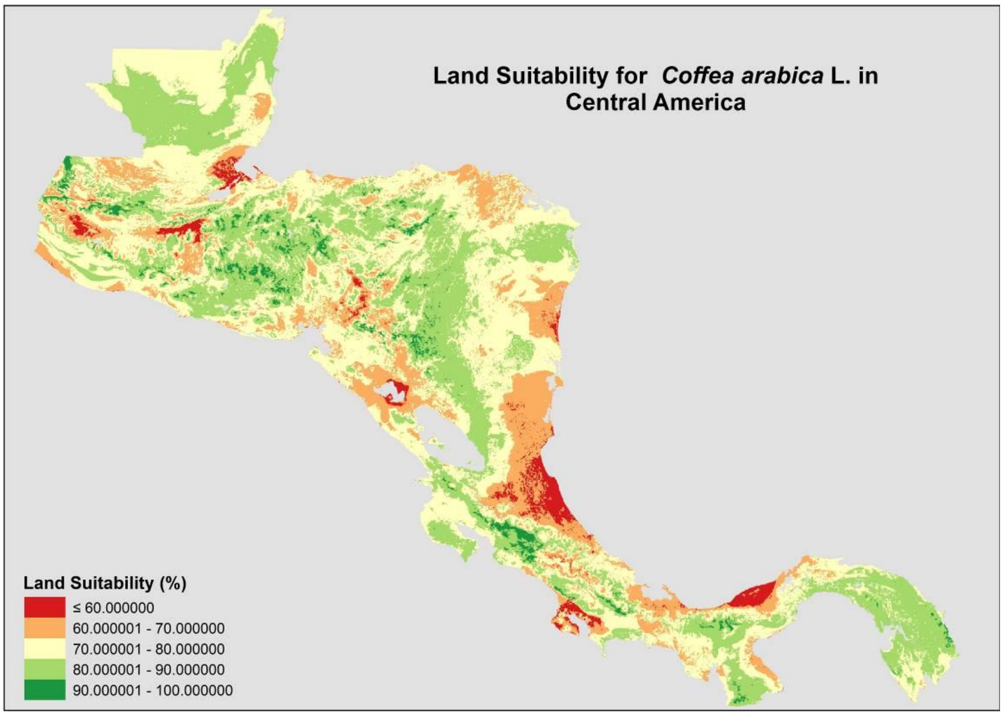


Figure A2. Map of current land suitability for Coffea arabica L. in Central America

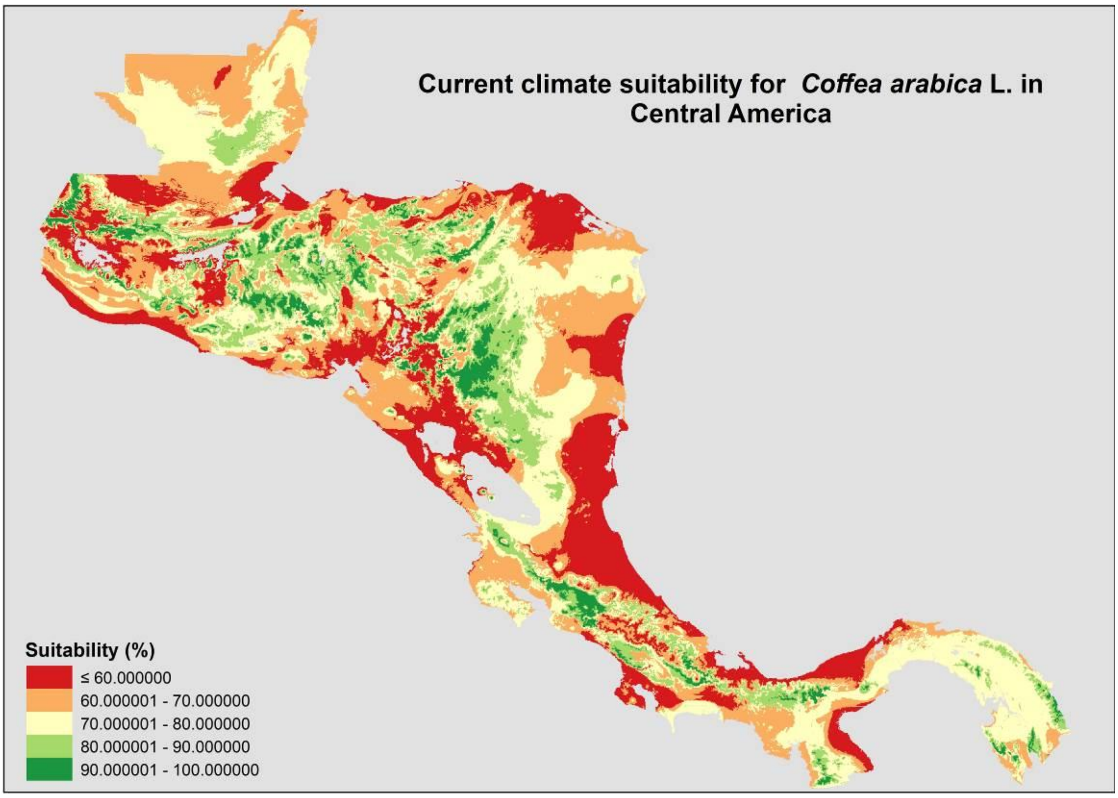


Figure A3. Map of current climate suitability for *Coffea arabica* L. in Central America

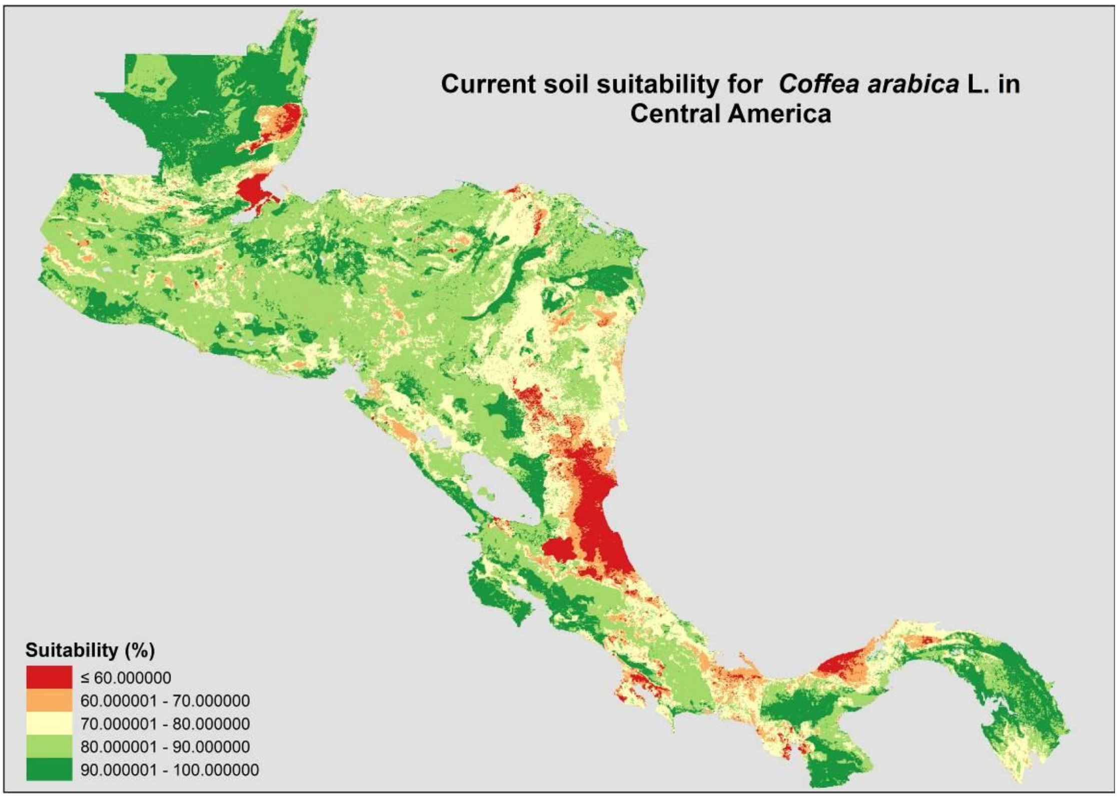


Figure A4. Map of current soil suitability for *Coffea arabica* L. in Central America

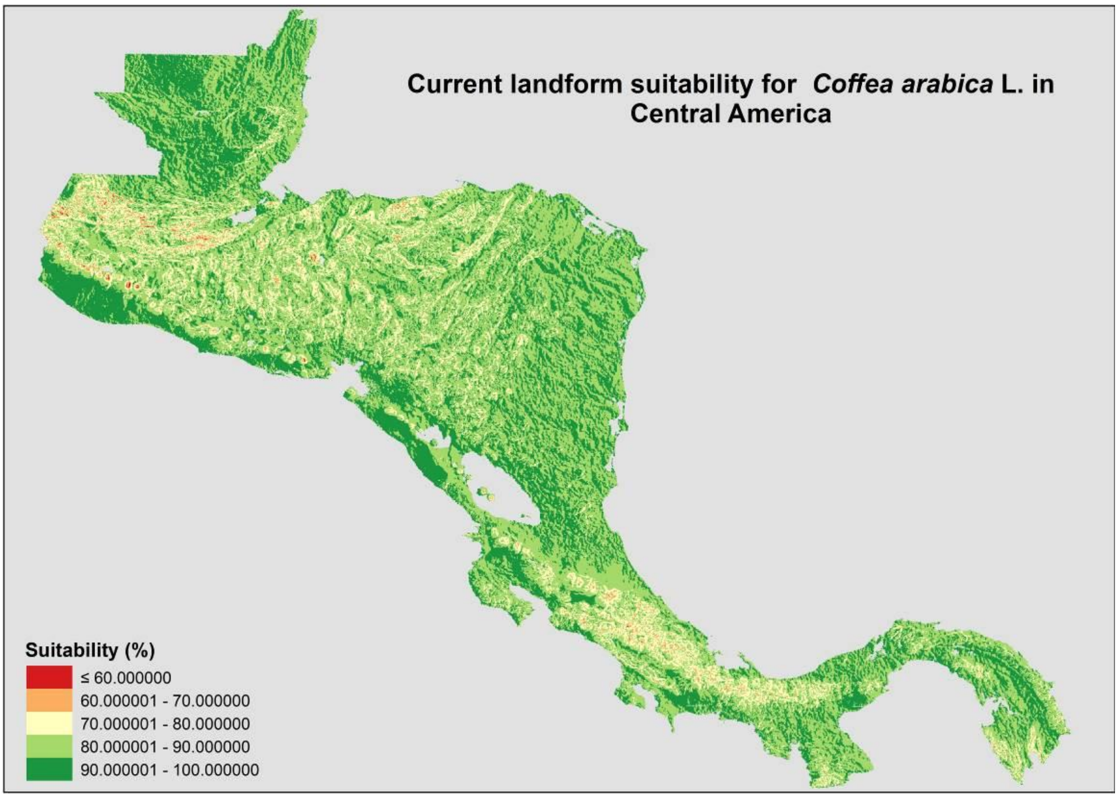


Figure A5. Map of current landform suitability for *Coffea arabica* L. in Central America

Appendix C. Distribution of coffee and non-coffee areas' land suitability in Central America

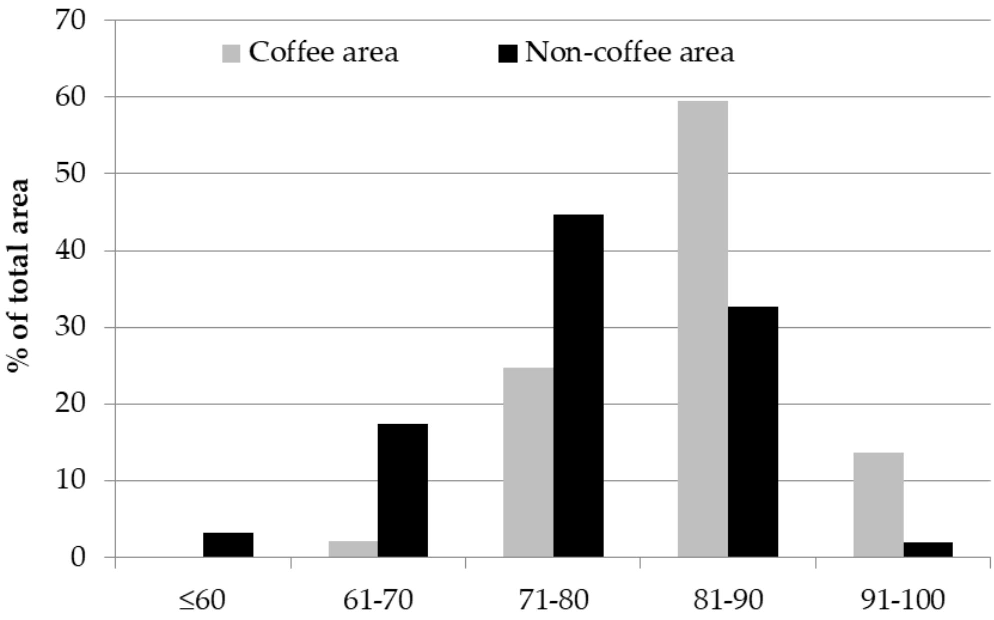


Figure A6. Simulated share of total coffee and non-coffee area in Central America in the different land suitability classes for coffee production.

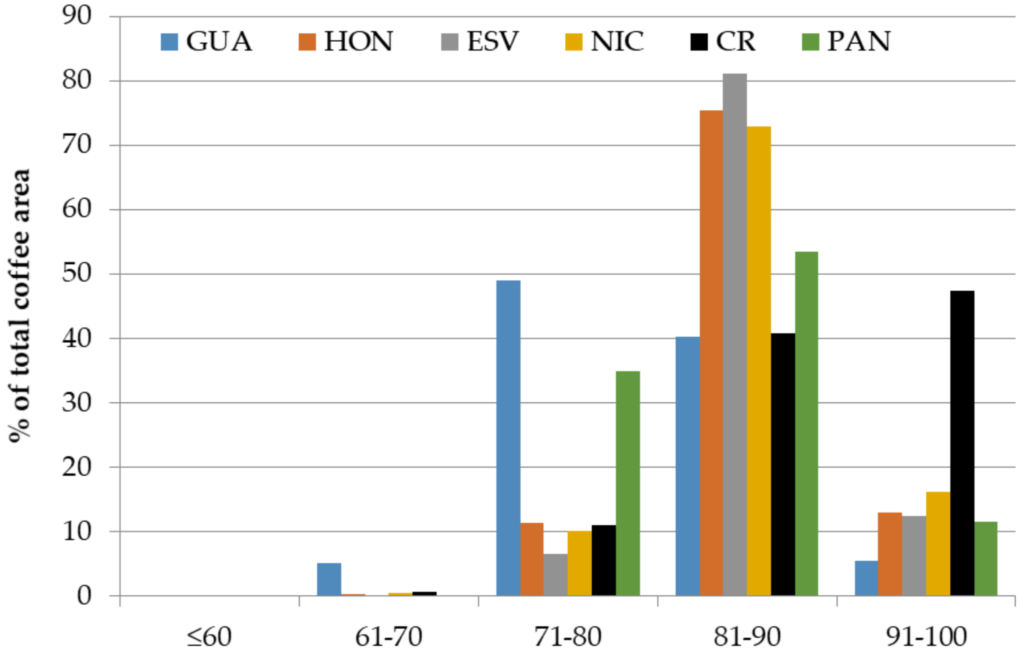


Figure A7. Simulated share of total coffee area in the countries Guatemala, Honduras, El Salvador, Nicaragua, Costa Rica and Panama in the different land suitability classes for coffee production.

3. CHANGES IN THE LAND SUITABILITY FOR *Coffea arabica* L. DUE TO CLIMATE CHANGE IN CENTRAL AMERICA

3.1. Introduction

In the last two decades, the coffee sector in Central America has experienced a drop in prices and coffee rust outbreaks; crises that have provoked a progressive diminishing of the sustainability of coffee production (Avelino et al., 2015a; CEPAL, 2002; PROMECAFE, 2018). Given the projections of drier and warmer conditions in the Northern, and wetter conditions in the Southern areas of the region under climate change (Hidalgo et al., 2017), a change in the climate suitability for coffee [*Coffea arabica* L.] is expected. Climate change may thus not only represent a new challenge, but even exacerbate existing ones, making it even more difficult sustain coffee production (Eakin et al., 2005; Frank et al., 2011).

Contrary to its wild relatives, coffee have been bred and selected for specific purposes, such as increase productivity, quality, or resistance to pests and diseases. As a cultivated plant, the coffee production requires farm planning and reach productive standards that merely survive and reproduce as occurred with coffee wild plants (Miller and Gross, 2011). So, production systems have been evolved to accomplish such productive purposes (Bertrand et al., 2011; Lashermes et al., 2009; Montagnon et al., 2012), existent land features [agroecological conditions: climate, soil, landforms], and farmers' socioeconomic conditions (Sys et al., 1991; Young, 1987). According to some authors the climate, soil, and landforms are responsible for about the 48, 36 and 15% of the land suitability for coffee production, respectively (Lara-Estrada et al., 2017; Mighty, 2015); which is in line with the accepted perception that coffee is sensitive to climate and mineral fertilization (Gay et al., 2006; Meylan et al., 2013). So, information over the land suitability for coffee will give farmers and agronomists better insights of the limitations that coffee cultivation will face in a particular piece of land and help to define farm planning that includes practices to overcome or alleviate such land's limitations; farming practices like the use of shade trees, soil management, adapted coffee varieties are some of them..

Previous studies had addressed the climate change effects only over the climate suitability for coffee using species distribution models (Bunn et al., 2014; Ovalle-Rivera et al., 2015) that initially were developed and used to study the dispersion patterns of wild species based on presence-only data (Guillera-Arroita et al., 2014; Phillips et al., 2006; Yackulic et al., 2013). Their results indicate losses about 50% of climate suitability for coffee in the region and suggest as a possible measure of action to move the current coffee areas upward to overcome the climate change alteration without considering other agroecological factors like soils or landforms. These studies were useful to give a first impression and raise awareness in the coffee community and consumers of the possible impacts. However, for planning purposes, an agronomical based approach is required; land suitability evaluations serve to this purpose by assessing the most critical agroecological factors that define the land potential to produce coffee. Including soil and landform together with climate variables offers a better description of the land to farmers, agronomist, and others decision makers during planning process than only consider climate (FAO, 1976; McRae and Burnham, 1981; Mighty, 2015; Nzeyimana et al., 2014). In this sense, the Bayesian network model for Agroecological Land Evaluation for *Coffea arabica* L. [ALECA] can evaluate the land suitability considering climate, soil, and landforms information (Lara-Estrada et al., 2017). ALECA was developed based on parameters reported in the coffee literature and empirical data. The model has been used to evaluate the current conditions for coffee production in Central America (Lara-Estrada et al., 2017). Hence, we used the model to evaluate the impact of climate change over the land suitability of coffee areas in Central America and address the use of the land suitability information for agricultural planning.

3.2. Methods

Our study area corresponds to the Central America region focusing on the current coffee areas. The model ALECA evaluates the land suitability using climate, soil and landform data: annual mean temperature [°C], annual precipitation [mm], dry season length [months], slope [%], aspect [cardinal direction], pH in H_20, cation exchange capacity [Meq 100 g^{-1}] and texture [categorical]. Given the unalterable nature of some of the variables [aspect, slope, and texture] or possible modifications using farming practices over others [CEC and pH], the soil and landform variables were assumed as unchanged; therefore, the dataset for current conditions [the reference year 2000] were used as well under climate change conditions. For details over the data, see section 2.2.2.3 (Hengl et al., 2014; Hijmans et al., 2005). In case of climate variables, the data from the model MPI-ESM-LR [ECHAM5] of the Max Planck Institute for the scenarios RCP 2.6, 4.5 and 8.5 for 2050 and 2080 were used (Jungclaus et al., 2006; Ramírez and Jarvis, 2008). The data were downloaded at 30 seconds resolution [~ 1 km] (Ramirez-Villegas and Jarvis, 2010) from the CCAFS GCM DATA PORTAL [http://www.ccafs-climate.org]. The MPI-ESM-LR was chosen because it performed as one of the best GCM modeling current conditions for the study region (Fuentes-Franco et al., 2015; Maloney et al., 2013; Schaller et al., 2011), and even better performance than the average value of others 20 climate models (Conde, 2011; Khatun et al., 2013).

Once the dataset was completed, the land suitability was inferred for coffee and non-coffee areas under the CC scenarios, where LS scores go from 0 to 100 %, where 100% is the highest optimal value. Also, a categorical land suitability scale was used to present the results: unsuitable = less than 60%, marginal = 60 to 75%, moderate = 75 to 85%, good = 85 to 90%, excellent = 90 to 100% (Lara-Estrada et al., 2017). The percentage and rate of change of LS between current and climate change scenarios for the coffee areas were estimated. The rate of change was estimated according to the FAO's equation used to calculate the annual rate of change [R_c] of forest to others land use by comparing the land use of a given area under two period [years] (Puyravaud, 2003; Velázquez et al., 2002). In our case, the equation depicts the R_c of coffee areas' land suitability between current conditions [2000] and climate change scenarios (2050 and 2080).

$$R_c = \left[\frac{A_2}{A_1}\right]^{1/n} - 1$$

Where the A_2 and A_1 are the areas [km^2] with a given LS-score, the n is the number of years between the two periods under comparison.

The LS-values for seven reference coffee zones we extracted and LS-changes calculated. The zones were used by Lara-Estrada et al. (2017) to validate ALECA and correspond to El Paraíso, Márcala [Honduras], Nueva Guinea, Masatepe, Jinotega [Nicaragua], San Carlos, Turrialba, and Tarrazú [Costa Rica].

Finally, we discuss the use of land suitability information to define adaptation strategies during farm planning.

3.3. Results and discussion

3.3.1. Regional coffee areas

The land suitability [LS] of current coffee areas decreased under the climate change scenarios in Central America. The areas under moderate and marginal-LS will increase at the expense of excellent and good ones (Figure 8 and Figure 9). There are no previous studies that approach the impact of climate change on the LS, so comparing our results to others studies was not possible. In the case of studies that reported climate suitability scores under CC, they are not comparable to our land suitability scores because the LS-scores integrate the suitability scores of the soil, landform and climate variables existing in the land under evaluation. The current land suitability scores of the soil, landform and climate conditions are available in Lara-Estrada et al. (2017), Chapter 2. Here we focus on the impact of climate change on the future land suitability.

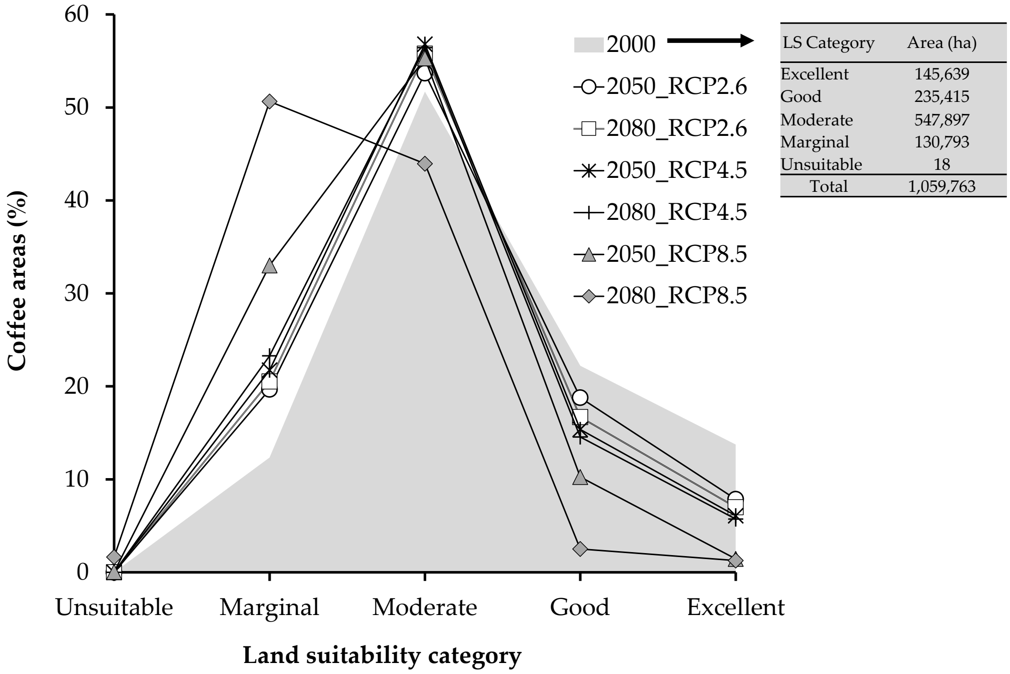


Figure 8. Current and future land suitability of coffee areas (*Coffea arabica* L.) under three scenarios of climate change in Central America. Land suitability score: unsuitable= less than 60%, marginal=60 to 75%, moderate=75 to 85%, good=85 to 90%, excellent=90 to 100%.

The results depict the evaluation of the environmental conditions; hence, the effect of the farming practices that already are implemented by farmers to improve the land suitability for coffee production are excluded. Some of these farming practices widely used in the region are the inclusion of shade trees in the coffee plantation to improve the microclimate and soil conditions [agroforestry], and soil conservation practices. These kinds of farming practices add layers of soil or climate suitability to the preexisting land conditions making possible the cultivation and occurrence of coffee areas under less suitable conditions; which in part explains the presence of an important portion of coffee areas under marginal LS. In Chapters 5, 6 and 7 we address the use of shade trees and its impact on the land suitability and coffee systems.

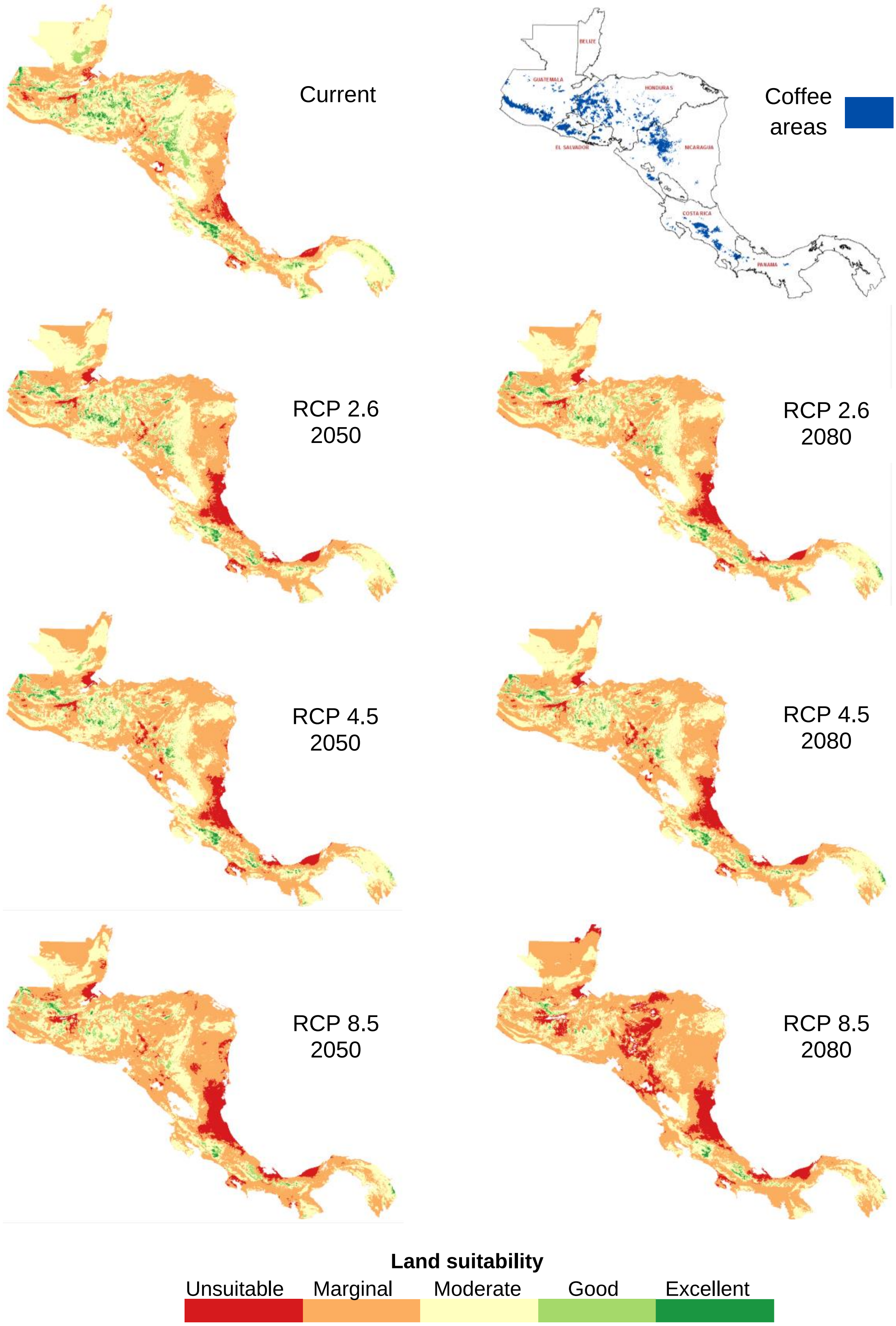


Figure 9. Current and future land suitability for *Coffea arabica* L. under three scenarios of climate change in Central America. Pixel size = 1 km. Land suitability score: unsuitable= less than 60%, marginal=60 to 75%, moderate=75 to 85%, good=85 to 90%, excellent=90 to 100%.

Since the data of soil and landform component were *ceteris paribus* under current and future conditions in this study, the observed changes in land suitability correspond to the effect of the alterations in the climate suitability. Here, coffee areas with marginal or moderate soil and landform suitability will lose more land suitability due to a downgrade in climate suitability than coffee areas with good or excellent soil or landform conditions [see 3.3.2]. From the three variables used to estimate the climate suitability, on average, the mean air temperature depicts the highest variations in suitability for coffee [scoring from -10.24 to 12.37%] among years and scenarios, then the annual precipitation [from -0.36 to -3.10%] and dry season length [from 0.05 to 0.32%]. However, if we observe the coefficient of variation, and the minimum and maximum values of the suitability scores for each variable, we can anticipate that some areas will suffer higher alterations in their suitability than others (Table 5). Therefore, next, we explore such dynamic of change in the land suitability.

Table 5. Descriptive statistic of the suitability scores for coffee of the variables mean air temperature, annual precipitation and dry season length under climate change in coffee areas in Central America.

RCP	Year	Variables	LS variation (%)	SD	CV	Min	Max
RCP2.6	2050	Mean Temperature	-10.24	11.31	110.43	-53.73	71.04
		Annual Precipitation	-0.36	10.23	2846.69	-34.75	49.57
		Dry Season Length	0.32	7.10	2234.46	-40.04	40.04
	2080	Mean Temperature	-9.34	10.73	114.95	-53.73	70.15
		Annual Precipitation	-1.50	8.05	538.38	-38.19	44.84
		Dry Season Length	0.39	8.36	2163.63	-40.04	40.04
RCP4.5	2050	Mean Temperature	-10.35	11.32	109.44	-53.73	56.24
		Annual Precipitation	-3.10	8.01	258.54	-39.28	32.12
		Dry Season Length	-0.55	7.43	1346.84	-40.04	40.04
	2080	Mean Temperature	-12.37	12.73	102.93	-57.76	72.66
		Annual Precipitation	-3.07	8.48	276.22	-37.72	44.94
		Dry Season Length	0.05	8.84	17121.33	-40.04	40.04
RCP8.5	2050	Mean Temperature	-23.33	17.35	74.40	-71.15	74.8
		Annual Precipitation	-2.19	10.36	473.82	-30.6	37.05
		Dry Season Length	1.77	9.18	518.3	-30.88	40.00
	2080	Mean Temperature	-47.27	21.37	45.20	-86.15	89.76
		Annual Precipitation	-6.17	10.20	165.31	-65.77	39.75
		Dry Season Length	0.13	12.29	9684.70	-75.15	40.00

LS = land suitability scores, SD = standard deviation, CV = coefficient of variation, Min = minimum, Max = Maximum

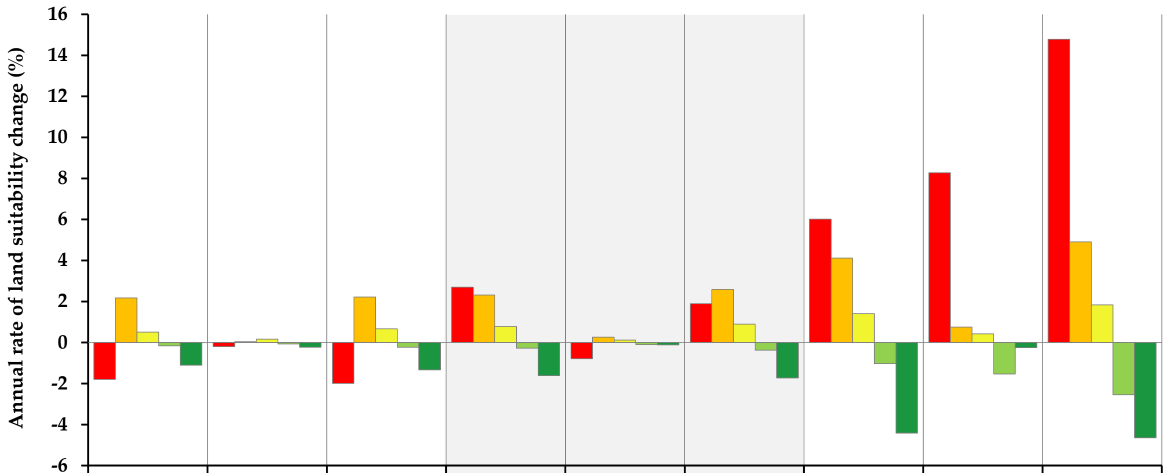
The changes in the land suitability of coffee areas occurred in both direction, upgrade and downgrade, and were time-dependent. Table 6 shows the tracking of land suitability changes [%] of the current coffee areas across time and climate scenarios. The coffee areas classified as excellent and good in the year 2000 are reduced to less than 50% under the scenarios RCP 2.6 and RCP 4.5, and between 8 and 17% under RCP 8.5 for 2050 and 2080; most of these areas become moderate and marginal. On the contrary, above of the 93% of marginal and 75% of moderate coffee areas remains in the same category –except under RCP 8.5 in 2080. The coffee areas that experienced an upgrade from marginal or moderate to excellent or good-LS were below 5%. Only under RCP 8.5 at 2080, the upgrades from marginal [89.49% of the area in 2000] and moderate [63.62%] to good were higher. Similarly, unsuitable areas upgrade [71%] to marginal; however, the change is irrelevant because of the actual size of the unsuitable areas in 2000 [18 ha] (Table 6 and Figure 8). Hence, in general, the dynamic of changes described a reduction of better suitable areas, and keeping up and increasing the moderate and marginal areas.

Table 6. Land suitability changes expected under future climate scenarios for current coffee areas in Central America.

Land Suitability	2050					2080				
	E*	G	Mo	Ma	U	E	G	Mo	Ma	U
Current \ RCP										
Excellent	45.3	32.7	21.9			43.9	30.0	25.9		
Good	3.66	52.6	43.5	0.19		2.37	49.0	48.3	0.24	
Moderate	1.58	5.00	77.9	15.4		0.84	3.19	78.7	17.2	
Marginal		0.09	5.70	94.2	<0.0		0.02	6.12	93.8	<0.0
Unsuitable				71.1	28.8				71.1	28.8
Current \ RCP										
Excellent	40.4	31.3	28.2			37.4	31.9	30.5		
Good	1.38	44.8	53.5	0.28		1.66	40.7	57.1	0.42	
Moderate	0.41	2.13	78.1	19.2		0.41	2.14	75.0	22.4	
Marginal		0.06	5.04	94.8	0.05			5.93	94.0	0.03
Unsuitable				71.1	28.8				71.1	28.8
Current \ RCP										
Excellent	8.43	32.2	59.0	0.31		7.23	4.44	12.5	75.7	
Good	1.01	17.0	79.0	2.94		0.88	27.4	2.09	69.5	0.06
Moderate	0.12	3.77	56.0	40.0		0.12	63.6	0.59	34.0	1.59
Marginal		0.66	5.01	94.0	0.25		89.4	0.12	3.86	6.53
Unsuitable			71.1		28.8				71.1	28.8

*Land suitability categories: E = excellent, G = good, Mo = moderate, Ma = marginal, U = unsuitable. Land suitability score: unsuitable = less than 60%, marginal=60 to 75%, moderate = 75 to 85%, good = 85 to 90%, excellent = 90 to 100%. Notice: The 100% of areas under the current conditions is obtained by summing row values. Values in gray cells show the ratio of areas that remain in the same land suitability category from one period to the next. The values to the right of the gray cells indicate a land suitability downgrade, the ones to the left a suitability upgrade. No change situations would be observing 100 in a grayed cell.

In addition to the dynamic of change, we calculated the annual rate of change (R_c) to depict the speed of the LS-changes [downgrade and upgrade] between years under the climate scenarios [2000-2050, 2050-2000 and 2000-2080] (Figure 10). Overall, the areas that scored LS above 80% in 2000 [equivalent to LS excellent and good, and some moderate] show negative rates of changes and areas with land suitability between 60-80% [marginal and some moderate] show positive rates under all the scenarios and periods evaluated. In the case of areas with LS below 60%, they display different rates of change depending on the scenario and period. Comparing the LS values between periods, we observed that the highest R_c of areas with good and excellent suitability occurred in 2000-2050 under the three RCPs [R_c Maximum = -4.42, R_c Minimum = -0.16]; then, the rate decreases in 2050-2080 [R_c Max. = -1.53, R_c Min. = -0.07] (Table 6, Figure 8 & Figure 10). In case of RCP 2.6 and 4.5, the highest rate of change under three scenarios occurs at 2000-2050, then a deceleration of the rate of change occurs at 2050-2080, and RCP 8.5 shows mixed results between periods (Figure 10). These changes imply progressive changes in the land suitability per year; for example, out of 145,639 ha of coffee areas classified as LS-excellent in 2000, about 1,617 ha per year are expected to downgrade to good or moderate until 2050, remaining only 45.36% of the areas under LS-excellent, then the trend slows down until reach 43.95% by 2080. This rate variation between periods responds to the warming effect of the RCPs over both periods (Table 5). According to the CMIP5 model, the global warming trend depicts a rising in mean air temperature under the three RCPs around of the middle of the century, then the trend stops under RCP 2.6 [warming ~ 1 °C], continues at a lower rate under RCP 4.5 [~ 1.8 °C], and increases under RCP 8.5 [~ 3.2 °C] until 2080 (Knutti and Sedláček, 2012).



LS scores	2000-2050	2050-2080	2000-2080	2000-2050	2050-2080	2000-2080	2000-2050	2050-2080	2000-2080
		RCP 2.6			RCP 4.5			RCP 8.5	
50 to 60	-1.80	-0.20	-1.99	2.70	-0.79	1.89	6.01	8.27	14.78
60 to 70	2.18	0.04	2.22	2.32	0.26	2.59	4.12	0.75	4.91
70 to 80	0.51	0.16	0.67	0.78	0.12	0.90	1.41	0.42	1.84
80 to 90	-0.16	-0.07	-0.23	-0.27	-0.10	-0.38	-1.03	-1.53	-2.54
90 to 100	-1.11	-0.23	-1.34	-1.61	-0.12	-1.73	-4.42	-0.24	-4.65

Land suitability under RCPs and periods

Figure 10. The rate of change of coffee areas between the periods 2000-2050, 2050-2080 and 2000-2080 under climate scenarios. The rate depicts the intensity and direction: gains (+) or losses (-). Notice the higher rates occurred in 2000-2050 under most of the climate change scenarios.

3.3.2. Reference coffee areas

Looking at the reference coffee zones gives us a sharper insight of the dynamics of LS-change at the local level (Figure 11), and confirms our previous comment on "some areas will suffer higher alterations in their suitability than others" based on regional results (Table 5). Under current conditions, the coffee areas of Tarrazú are considered as LS-excellent, Jinotega, and Márcala as good, El Paraíso, Masatepe and Turrialba as moderate, and San Carlos and Nueva Guinea as marginal (Lara-Estrada et al., 2017). For more details about the current conditions of soil, landform and climate see the content relate to reference zones in section 2.4 (Lara-Estrada et al., 2017). Our results show that most zones will downgrade their LS, but some will downgrade more than others, and others will even experience slight upgrades under the less severe scenarios. Tarrazú, Jinotega, and Márcala will downgrade the least [-4%], and even Tarrazú and Márcala may experience some minor upgrades in LS under the less severe scenarios [RCP 2.6 and 4.5]. Turrialba and Masatepe will experience the highest loss of LS under the RCP 2.6 and 4.5 (Figure 11).

Under RCP 8.5, except Tarrazú, all the coffee areas experience the most substantial LS reductions of the three RCPs. Therefore, most of the reference zones may become marginal or unsuitable under RCP 8.5 by 2080 (Figure 11).

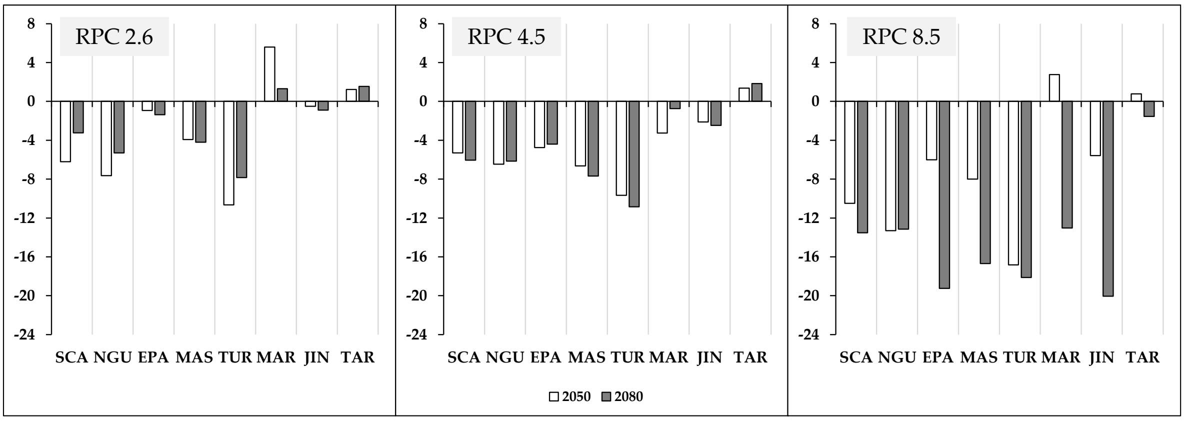


Figure 11. Expected land suitability changes for seven coffee reference zones in Central America. EPA=El Paraíso, MAR=Márcala; Nicaragua: NGU=Nueva Guinea, MAS=Masatepe, JIN=Jinotega; Costa Rica: SCA=San Carlos, TUR=Turrialba, TAR=Tarrazú.

3.3.3. Adapting to the land suitability changes

Given the LS-downgrade foreseen to 2050 (Table 6), actions need to be implemented in a timely manner. Some authors have pointed out that moving the coffee areas to higher altitudes may be a solution to compensate for the warming conditions (Läderach et al., 2010; Zullo et al., 2011); and some areas currently not suitable for coffee will become suitable in the future (Figure

9 and Figure A8). But given the history, current dynamics of land use change and land regulation in the Central American countries, such strategies may not be realistic (Blackman et al., 2006; Boucher et al., 2005; Broegaard, 2010; Charlip, 1999, p. 1999; Zeledon and Kelly, 2009). Instead, Haggar and Schepp (2012) mention a series of adaptation strategies that include technical, financial, and organizational aspects that farmers and farmers' organization can ponder and implement to improve their level of resilience to climate change effects. In this sense, and considering our land suitability approach, the adaptation strategies should include practices and technologies that improve the land and coffee plantation conditions. Some of these practices and technologies include agroforestry [which provides goods and services], conservation of soil and water, and better-adapted coffee varieties (Blanco and Aguilar, 2015; Harvey et al., 2014; Lashermes et al., 2009). Agroforestry is widely used in the coffee areas in the region; however, the modification in the structure, composition and shade level of the tree component might need to fit the CC conditions. Also, the use of better-adapted varieties to shading, drought and warming conditions are an option to improve the resilience of coffee farms under marginal and moderate LS conditions (Bertrand et al., 2011; Montagnon et al., 2012).

The adaptation strategy [selection of practices and technologies] should be integrated into the farming strategy of each coffee farmer. This integration can occur under an agroforestry planning process (Somarriba, 2009; Vega and Somarriba, 2005) that consider the current and expected states of the land components [soil, landform and climate] and coffee plantation, past and latent risks for coffee production [coffee rust, price crisis, local land use change tendencies], diversification alternatives, and the farmers' socioeconomic conditions and preferences under an agroecological scope.

Based on the variability in speed and severity of the LS-changes in the reference coffee zones [local level], the policies and support programs to farmers and farmers' organizations should consider capturing such variability and facilitate the legal, technical and financial tools to plan and implement the farming strategies. For example, under the less severe scenarios, coffee areas with coffee quality reputation like Tarrazú, Jinotega, and Marcala that are expected to experience slight LS-downgrade might need to only adjust their coffee farming strategy [practices and technologies] to fit the new conditions, passing from a farming strategy based on "coffee quality" to a strategy more oriented to "quantity". On the other hands, coffee areas with higher LS-downgrades will be forced to implement major adjustments or even shift to other crops or land production systems (Vermeulen et al., 2013).

Finally, due to the magnitude of the changes in the land suitability across the coffee areas in the region, even the coffee adaptation actions were implemented in time, and the coffee production continues in the region, the amount of coffee produced and the quality profile of the region will be affected negatively.

3.4. Conclusions

Climate change will downgrade the current climate suitability and consequently the land suitability of the coffee areas in Central America; even the less severe scenarios will reduce the suitable areas significantly and increasing the marginal and moderate areas. Under the worst climate change scenario, most of the coffee areas will become marginal or unsuitable for coffee (*Coffea arabica* L.).

Given the expected rate of land suitability downgrade by 2050 and the perennial nature of the coffee plant, most of the actions to adapt the coffee farmers have to be implemented in short. Such actions should be integrated into a planning process that considers the current and future conditions of the main biophysical productive factors as well as socioeconomic and market factors that lead to possible farming strategies for farmers. Under these planning processes, the land suitability evaluations provide valuable information on the primary productive factors to decision makers and farmers.

3.5. Appendices III

Appendix III-A. Published suitability evaluations for Coffea arabica L.

Table-A 1. Published suitability evaluations for *Coffea arabica* L. and their capability to deal with different type of uncertainty.

Studies	Variables considered			Type of uncertainty		
	Climate	Soil	Landforms	Parameters	Input data	Output data
ALECA	X	X	X	X	X	X
Mighty (2015)	X	X	X			
Nzeyimana et al. (2014)	X	X	X			
Bunn et al. (2014) / Ovalle et al. (2015)	X			X		X

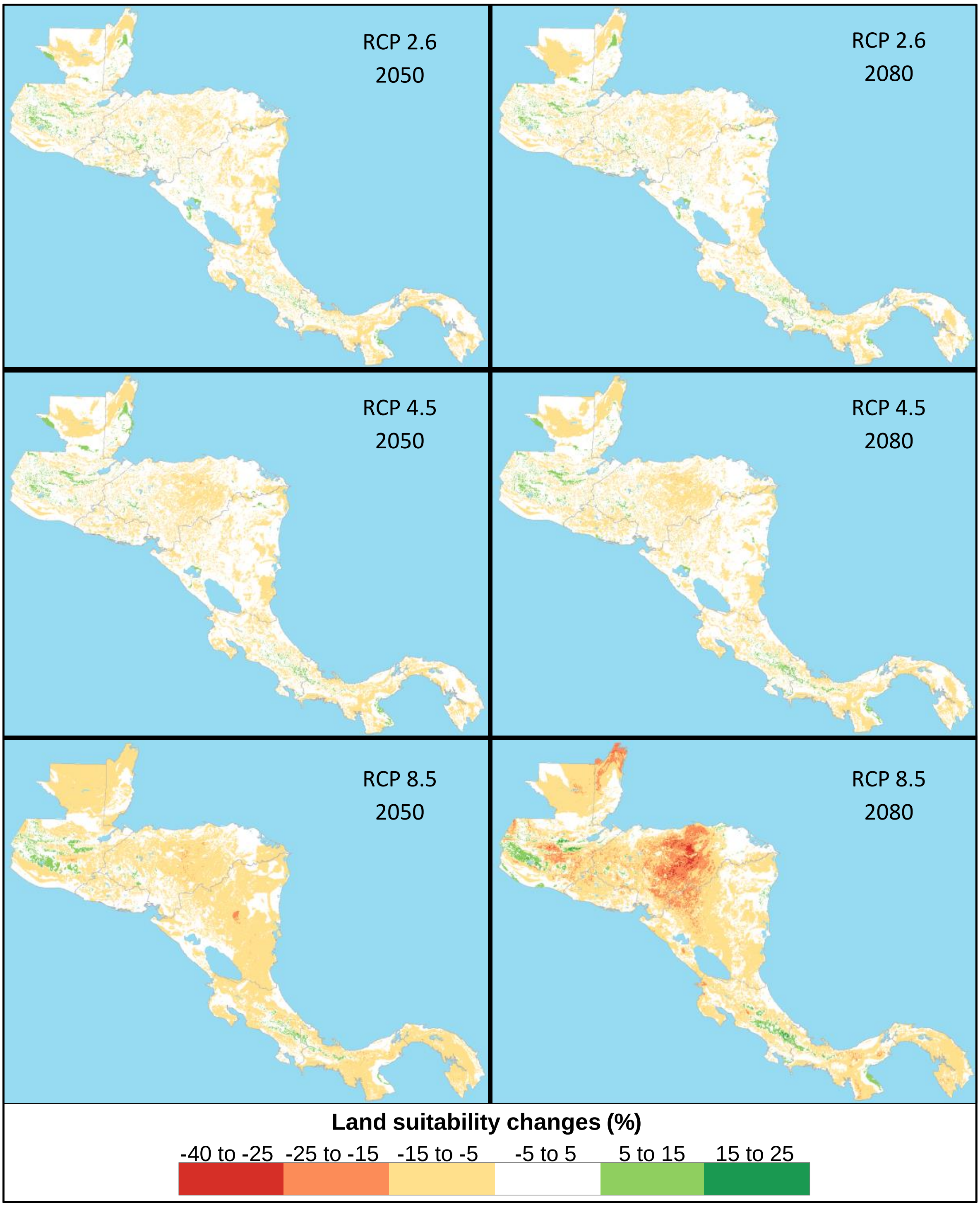


Figure A8. Expected land suitability changes for coffee production in Central America under climate change. Reference year: 2000. Notice changes inside of each legend's land suitability ranges occur.

4. INFERRING MISSING CLIMATE DATA FOR AGRICULTURAL PLANNING USING BAYESIAN NETWORKS[3]

4.1. Introduction

Missing data is a major challenge for agricultural planning, reporting and research not only at the level of individual farms, but also at regional, national, or international scales. Incomplete information leads to misrepresentation and bias, but collecting the missing data can be very costly (Little and Schenker, 1995; Miller et al., 2010). Several procedures have been employed in previous applications to deal with data gaps. For example, the Agricultural Resource Management Survey in the USA uses conditional or national averages with or without outliers (Miller et al., 2010). In agricultural research, data gaps have been filled by combining survey and satellite information (Frolking et al., 2002), spatial interpolations (Smith et al., 1996), introduction of proxy variables (Liu and Scott, 2001), and, in the case of climate research, by using the regularized EM algorithm for Gaussian data (Schneider, 2001), empirical orthogonal functions (Smith et al., 1996), grouping methods of data handling (Acock and Pachepsky, 2000), and others.

A scarcity of data, data with a high uncertainty attached or inhomogeneous data from different sources is especially prevalent in developing countries. While the procedures described above are mostly suitable for dealing with the problem, their practical implementation in developing countries is often difficult due to a lack of qualified personnel and financial shortfalls (Harris, 2004; Wagner et al., 2001; World Bank., 2013). For example, in several Central American countries, the reconstruction of climate variables using interpolation methods was only possible with external funding from the World Bank (World Bank., 2013). To overcome these hurdles, we propose to use a Bayesian network (BN), which is a mathematical model that graphically represents conditional probabilistic dependencies between variables. BNs can deal with uncertainty, missing data, missing (hidden) variables and small datasets; it is possible to learn the graphical structure and the parameters of the model from data, literature, expert knowledge or a combination of all (Aguilera et al., 2011; Barton et al., 2012; Sucar, 2015a; Uusitalo, 2007).

---

[3] Lara-Estrada, L., Rasche, L., Sucar, L.E., Schneider, U.A., 2018. Inferring Missing Climate Data for Agricultural Planning Using Bayesian Networks. Land 7, 4. https://doi.org/10.3390/land7010004

Another practical advantage of using BN is the availability of free software (Kevin Murphy, 2014; Mahjoub and Kalti, 2011).

In a BN approach, data can be generated for variables with missing values while maintaining a consistent relationship with other variables in the same dataset (Cano et al., 2004). It also allows the user to incorporate the uncertainty surrounding input data by entering a range or distribution of possible values or by using the prior information parameterized in the model when no information is available. Instead of a single, certain value, the output is then the most probable value of the variable of interest with the uncertainty attached (Aguilera et al., 2011; Norsys, 2015; Uusitalo, 2007). The Bayesian ability to handle uncertainty in the modeling process is advantageous, considering that uncertain and missing data are common in real-world situations (Andradóttir and Bier, 2000), especially when dealing with climate variables and when working in regions without good data coverage (De la Torre-Gea et al., 2011; Fang et al., 2009; World Bank., 2013).

There are several options in BNs for dealing with missing data: removing the registers with missing values; using mode values in place of the missing values or estimating the missing values based on the values of the other variables in the corresponding register using probabilistic inference (Sucar, 2015a). The last option has the advantage that the complete dataset is used, and that specific values are estimated for the missing registers instead of only a measure of central tendency like the average or median. Therefore, in our approach, we estimate the missing values based on proxy variables and probabilistic inference. As a case study, we created a novel Bayesian network model to estimate the relative humidity for Central America and Southern Mexico. In order to build the model, we used machine learning algorithms available in the Bayesian networks approach to define the model's graphical structure and parameters from monthly relative humidity data (Friedman et al., 1997; Norsys, 2015; Spiegelhalter et al., 1993). We then applied the model to infer values for relative humidity under two conditions: using a complete set of input information, and incomplete information, where one or two of five proxy variables were unavailable. The second scenario shows the capability of BN models to produce results even when information is missing. In both scenarios, monthly relative humidity and the Relative Humidity of the Driest Month (RHDM) were inferred. RHDM is one of the main variable-indicators to describe the land suitability for Coffee arabica L. production (Descroix and Snoeck, 2004).

A comparison of BN-estimated and reported values of monthly relative humidity and RHDM shows a high level of agreement between the values. The results also indicate a high level of consistency in the relationship between estimated relative humidity and proxy variables, which is one of the major concerns in modeling climate data. We conclude that the proposed method is a practical solution for estimating relative humidity, as it is based on information that is readily available and does not require high computational resources or technical expertise. Furthermore, estimating climate data for agricultural planning constitutes an important and unexplored domain for the application of probabilistic graphical models, which have only been used in climate science for weather forecasting (Cofiño et al., 2002) and to explore the dependencies between climate variables so far (De la Torre-Gea et al., 2011). Thus, this study forms an important contribution to the literature of BN applications and offers a valuable tool for coffee planning in Central America.

4.2. Methods

4.2.1. Study area

The study region, consisting of Central America and Southern Mexico, is located in the tropical zone, where the temperature remains relatively constant throughout the year and changes in season are driven by changes in precipitation. The prevalence of high water vapor contents and tropical temperatures leads to a high relative humidity (Peixoto and Oort, 1996; Taylor and Alfaro, 2005). The climatic conditions are favorable for coffee production, and most countries in the region are recognized for their high-quality coffee and shaded coffee systems (Avelino et al., 2005, 2002; Bertrand et al., 2006; Somarriba et al., 2004; Vaast et al., 2004), together producing more than 10% of the total global coffee supply (Bertrand and Rapidel, 1999; ICO, 2015). However, projections of climate change show that the region is likely to experience severe alterations in climate in the future, which may negatively impact coffee production (Gay et al., 2006; Haggar and Schepp, 2012; Läderach et al., 2010).

4.2.2. Relative Humidity

Relative humidity describes the water content in the air (Primault, 1979) and is normally calculated from the ratio between the saturation vapor pressure and the vapor pressure at a specific temperature (Harrison, 2014; Lawrence, 2005). Relative humidity has been identified as a key factor for coffee quality during the postharvest-storage (Ribeiro et al., 2011; Rojas, 2004) and as an agroecological variable that influences the suitability of a site for coffee production (DaMatta et al., 2007; Descroix and Snoeck, 2004). For example, values of RHDM between 50–60% are considered optimal, and values below 20% or above 80% as suboptimal for coffee cultivation (Descroix and Snoeck, 2004). Measurements of relative humidity are done using hygrometers in weather stations; however, this type of measurement is more expensive than measuring temperature or precipitation and therefore done far less frequently. To close the data gap, the development of modeling tools to estimate humidity based on other measured variables is a feasible strategy (Eskelson et al., 2013; Peixoto and Oort, 1996). In this study, we model the variable monthly relative humidity and relative humidity of the driest month, i.e., the month with the lowest precipitation.

4.2.3. Data

Variables experimentally observed or produced by reanalyses retain consistency among themselves. In our approach, we exploit this correlation to build and parameterize a Bayesian network model for inferring missing values for the relative humidity values from other climate variables. As a data source, we use the surface reanalysis dataset Climate Forecast System Reanalysis (CFSR) (Fuka et al., 2014; Saha et al., 2010). CFSR1[4] includes daily values for the variables precipitation (mm), air temperature (°C, minimum and maximum at 2 m), wind speed (m/s, at 10 m), surface solar radiation (MJ/m2) and relative humidity (%, at 2 m). The spatial resolution is 38 km × 38 km per pixel and data are available from 1979 to 2014.

We downloaded a set of daily data of all variables, covering Central America and Southern Mexico (a total of 855 pixels) for the years 1979 to 2000. From this dataset, a monthly subset MRH was created by aggregating the daily to monthly data for each year and pixel (n = 225,720). Then, a second subset RHDM was created by extracting the data (cases) of all the variables for the driest months of each year (n = 18,810). Summary statistics for the variables of both datasets were calculated (Table A2): The data distribution for humidity is different in both datasets, with μ = 77.79 and 69.13, and σ = 9.66 and 9.08 for the MRH and RDHM datasets, respectively, and in the RDHM dataset, the shape of the humidity distribution is more skewed to the left (Figure 12). The distribution of precipitation also differs markedly between both datasets (μ = 8.13 and 1.05, and σ = 8.38 and 1.79 for MRH and RDHM datasets, respectively), whereas only minor difference can be found for solar radiation, maximum and minimum temperature, and wind speed.

---

4 https://globalweather.tamu.edu/

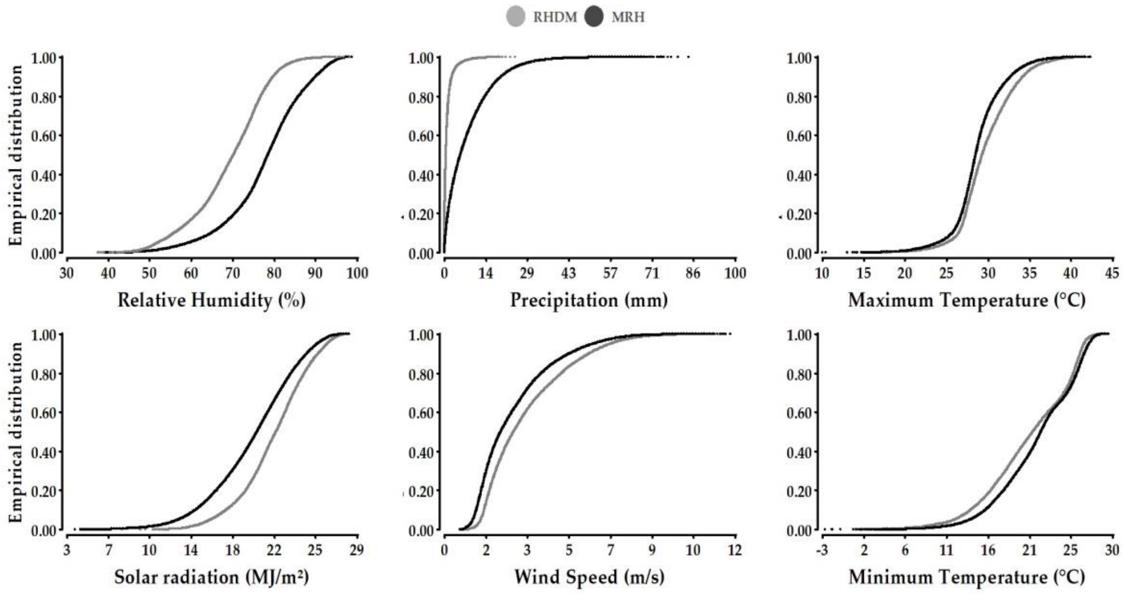


Figure 12. Empirical distributions of monthly relative humidity, precipitation, maximum and minimum temperature, solar radiation and wind speed from the datasets MRH and RHDM (n = 225,270 and 18,810, respectively). MRH: Monthly Relative Humidity; RHDM: Relative Humidity of the Driest Month.

4.2.4. Variable Selection

An exploratory analysis using principal components was done to identify which variables should be included in the model. For this, the complete dataset MRH was used (n = 225,270). The two first principal components explained 91.7% of the data variability (PC1 = 75.5% and PC2 = 16.2%) (Figure 13). Relative humidity has a positive correlation to precipitation (PRCP), and a negative one to TMAX and solar radiation (Solar) (PC1). Under intermediate conditions of precipitation and solar radiation, wind and TMIN have a major influence on the range of relative humidity (65–85%, PC2). With the exception of TMAX, relative humidity has a non-linear relationship with the proxy variables (Figure A9). Since all proxy variables thus influence relative humidity in different situations, we included all in the model.

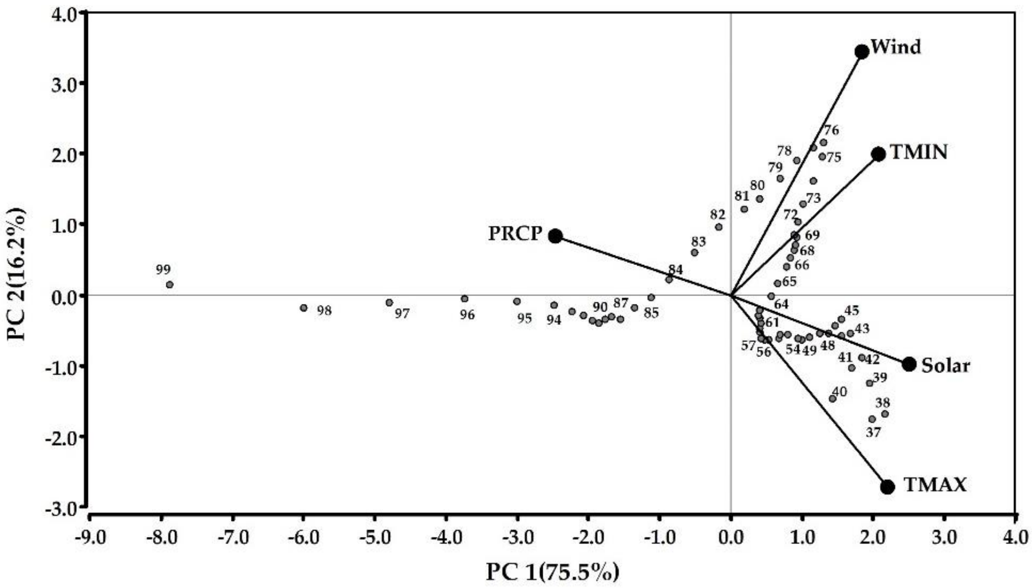


Figure 13. Principal component analysis including precipitation (PRCP), maximum temperature (TMAX), minimum temperature (TMIN), solar radiation (Solar) and wind speed (Wind) using monthly relative humidity (MRH) categorical values as the classification variable (n = 225,720). Gray dots and attached numbers correspond to MRH categorical values.

4.2.5. Discretization

The model was built using the software package Netica (Version 6.04, Norsys Software Corp., Vancouver, BC, Canada), which is free for small models with less than 15 variables. For each selected variable, nodes were created and discretized. The discretization of continuous variables in BN leads to the loss of information (Aguilera et al., 2011). An accepted strategy to deal with this is to mimic the data distribution of the variables in the discretization (Allan et al., 2012; Nojavan A. et al., 2017); however, the definition of the breakpoints for each state is a major challenge (Marcot et al., 2006; McCann et al., 2006; Nojavan A. et al., 2017). There are automatic methods to discretize continuous variables, but the selection of one method over another based on their performance is not clear, and using automatic methods may result in a discretization inappropriate for the purpose of the model and the users. For this reason, expert knowledge remains the best option for discretization (McCann et al., 2006; Nojavan A. et al., 2017; Uusitalo, 2007).

Here, we seek to estimate monthly relative humidity and the relative humidity of the driest month using a single model. The data distribution for precipitation is narrower for RHDM than for MRH (Figure 12 and Figure A9) and thus requires shorter breakpoints to gain enough precision to infer the relative humidity under dry conditions. We, therefore, split the states into two: for the lower values that correspond to the data distribution of the cases[5] of RHDM the breakpoints are shorter, and for the remaining range, the breakpoints are further apart. For the other proxy variables, intervals of equal length were implemented focusing on reproducing the distribution of the data. States were merged if the resulting states had a frequency distribution close to zero. The number of states of each variable was also based on the level of influence of this variable on relative humidity (see Section 4.3.1); the less influence, the less states were defined, thus contributing to reducing model complexity without loss of performance (Figure 14).

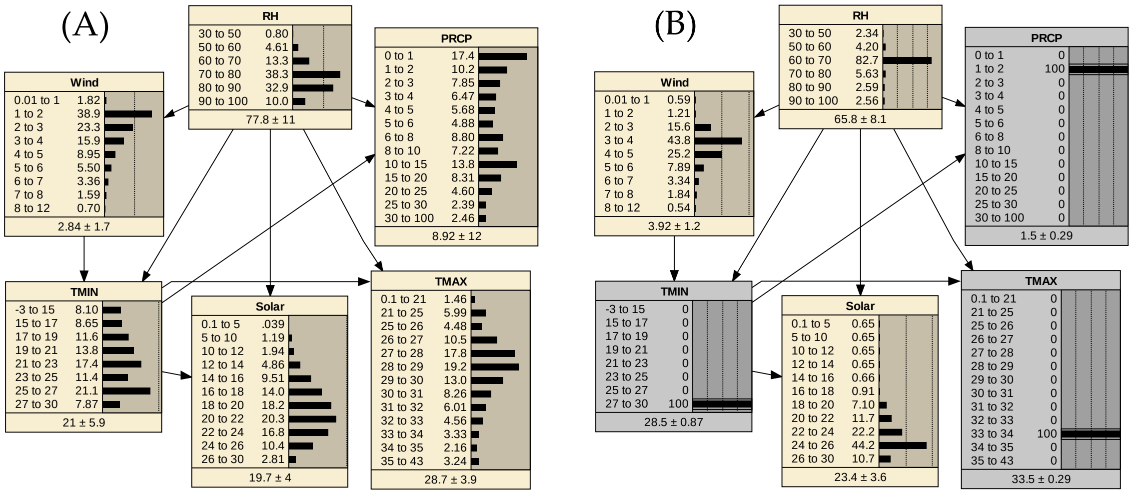


Figure 14. The Bayesian network model to infer monthly relative humidity. (A) Compiled model without evidence entered; (B) Model state when model is inferring the relative humidity of the driest month using only three proxy variables. Grey boxes indicate that evidence (values) were entered for the corresponding variables; the model uses the available new information to update the states of the remaining unknown variables (Wind, Solar, RH). RH: relative humidity (%), TMAX: maximum temperature (°C), TMIN: minimum temperature (°C), PRCP: total precipitation (mm). Graphical structure and parameters learned from the reanalysis dataset CFSR (Fuka et al., 2014; Saha et al., 2010).

We used the metric Spherical Payoff[6] to evaluate the contribution of a change in range or the number of states on model performance. If a change in the state's range or number of states performed better, the change remained.

---

[5] A case is the set of values of the proxy variables and relative humidity for a given month per a given pixel. For example, in the Figure 14B, the case entered in the net has values only for three variables.

[6] The Spherical Payoff is a scoring metric used to test the performance of Bayesian network models. The score goes from 0 to 1, where 1 is the best performance (Marcot, 2012).

4.2.6. Model Structure and Parameters

Once the node variables were discretized, the graphical model was learned from 80% of the cases of the dataset MRH (n = 180,530). The relative humidity node was set as the target variable, and the machine learning algorithm Tree Augmented Naive Bayes (TAN) was used to learn the model structure (Figure 14). TAN is a Bayesian classifier that incorporates dependencies between attributes by building structures between them (Friedman et al., 1997). The TAN algorithm drew edges from relative humidity to each proxy variable, and added extra edges between proxy variables. Using the same 80% of the MRH dataset, the Bayesian Counting—Learning Algorithm (Norsys, 2015) was used to learn the parameters –prior and conditional probabilities- of all variables in the model. The Counting—Learning Algorithm allows the model to move from initial-ignorance mode to parameterized mode by calculating the conditional probabilities and experience (confidence of the conditional probabilities) of the corresponding combination of variables' states (Norsys, 2015; Spiegelhalter et al., 1993). Once the parameter values are learned, the model can be compiled and is ready for use. An online version of the model is available at the following link: https://dev.hed.cc/?s=HR

4.2.7. Sensitivity Analysis and Model Validation

After compiling the model, we did a sensitivity analysis using the variance reduction procedure. The variance reduction estimates the impact of a change in the state of a proxy variable on the state of the target variable (Marcot, 2012). The variance reduction values range from 0 to 100%, where a higher value indicates a higher influence (Marcot et al., 2006; Norsys, 2015).

We validated the model in two ways. First, we tested the ability of the model to infer the monthly relative humidity of any given month in the year and the specific relative humidity of the driest month for the same period using all the proxy variables (PRCP, TMAX, Solar, Wind, and TMIN). Second, we explored the capability of the model to infer relative humidity with the variables Solar and Wind missing, which are hardly registered in the study region's weather stations (Figure 14B). The output value in the second case is the expected value, which is the mean of the possible states, weighted by their probability of occurrence (Norsys, 2015). As input data, we used the remaining 20% of the cases of the MRH dataset (n = 45,190) for inferring monthly relative humidity, and all the cases of the RHDM dataset (n = 18,810) for inferring the relative humidity of the driest month. Then, we compared the inferred to the observed values. For this, we used the metrics RMSE and bias (Badescu, 1993; Marcot, 2012). Finally, we provide a spatial comparison between the inferred and reported values described above, and suitability maps of the relative humidity of the driest month for *Coffea arabica* L. for the entire study region.

4.3. Results and Discussion

Climate variables dynamically interact at the same time and space, and some of these interactions are non-linear relationships. Being able to define our model structure and parameters using learning algorithms was therefore a significant advantage of the Bayesian network approach, which allowed us to capture this natural complexity in a simple explicit graphical model (Figure 13, Figure 14 and Figure A9).

4.3.1. Sensitivity Analysis

The sensitivity analysis (variance reduction) shows that precipitation and maximum temperature have the highest influence on relative humidity, followed by solar radiation, wind speed and minimum temperature (Table 7). This is expected, as relative humidity is a measure of the water content of air and variations in precipitation will influence this water content (Harrison, 2014; Magaña et al., 1999), and higher temperatures in tropical regions boost evapotranspiration processes, which release water to the air. Despite the low influence of TMIN on relative humidity, the variable has a strong influence on Wind, Solar and TMAX (Table 7), which is a result of the edges added by the TAN algorithm during the structure learning step. The influence between proxy variables is relevant in situations where a variable is unknown. The model can use the known proxy variables to update the states of the remaining unknown proxy variables and the relative humidity (Figure 14B), facilitated by the implicit representation of the joint distribution of the model obtained from the structural and parameter learning (Friedman et al., 1997; Spiegelhalter et al., 1993). The variables PRCP, TMAX and TMIN are thus the most influential in the entire network, and are required by the model to produce enough evidence to obtain good estimates for relative humidity.

Table 7. Results of the sensitivity analysis using variance reduction *

Proxy variables	Target variables RH	PRCP	TMAX	Solar	Wind	TMIN
RH	-	25.20	29.30	22.80	18.50	4.68
PRCP	41.80	-	7.70	3.22	0.89	5.42
TMAX	33.90	6.67	-	17.60	7.41	29.60
Solar	17.90	2.36	16.00	-	16.60	21.50
Wind	13.70	2.18	1.73	19.10	-	24.90
TMIN	1.94	3.09	24.20	28.60	45.90	-

* Variance reduction values go from 0 to 100, where a higher score indicates a higher influence on the target variable. Variables: Relative humidity (RH), precipitation (PRCP), maximum temperature (TMAX), minimum temperature (TMIN), solar radiation (Solar), and wind speed (Wind).

4.3.2. Validation

The expected values of monthly relative humidity and relative humidity of the driest month were inferred using (1) complete cases for all proxy variables, and (2) incomplete cases, where data of specific variables were missing, in our case once Wind, and once both Solar and Wind. In general, when comparing inferred values to reported values (Table 8) the metrics bias (less than the unit) and RMSE (<5%) indicate a very close agreement between values. As expected, the best model performance was obtained when information on all proxy variables was available; however, even under conditions of missing variables, the results were still very good (Table 8 and Figure 15). The only observable effect of missing variables was a lower model performance when estimated relative humidity values were <60%, which could be the result of the low number of cases in the MRH training dataset in this range (5.3% of total cases; 6 cases at 30–40%, 361 cases <50%, and 2060 cases <60%). Therefore, for some combinations of variable states, there were very few cases defining the conditional relationships (experience) between the variables, and the missing variable conditions increased the uncertainty during the inference.

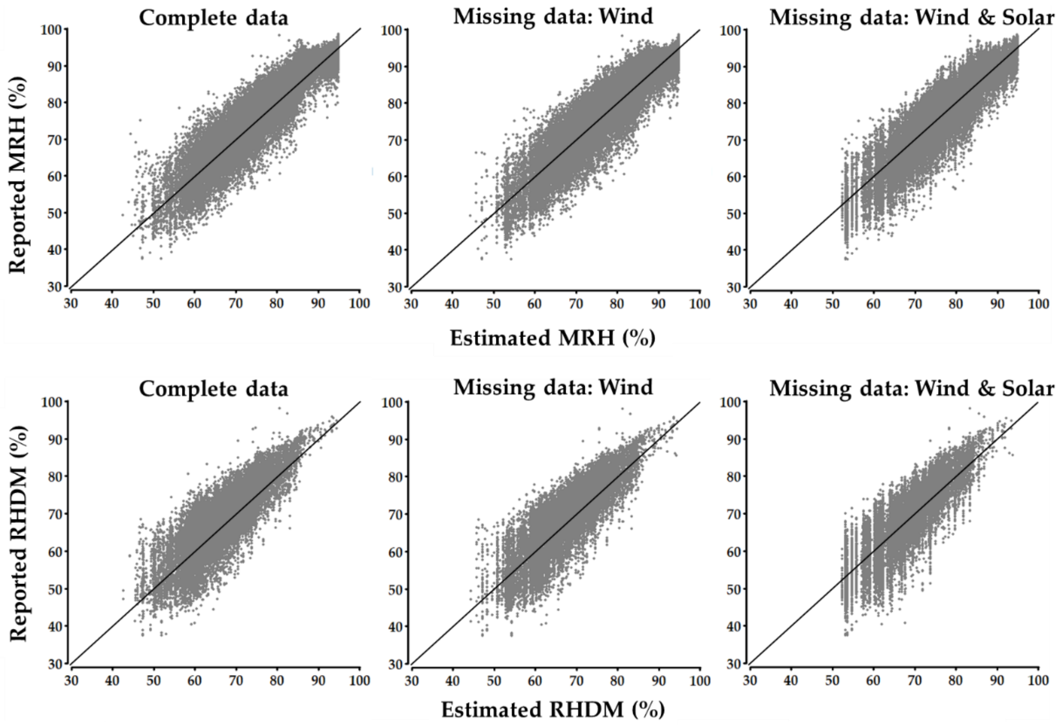


Figure 15. Scatter plot of model-estimated vs. reported values of monthly relative humidity (MRH) and relative humidity of the driest month (RHDM) using complete and incomplete data. Wind: wind speed, and Solar: solar radiation. Data source: reanalysis dataset CFSR (Fuka et al., 2014; Saha et al., 2010).

Table 8. Model performance inferring the monthly relative humidity (MRH) and the relative humidity of the driest month (RHDM) using proxy variables.

Inferred variable	Cases (dataset)		Proxy variables**		Metrics	
	Model building*	Validation	Known	Missing	BIAS	RMSE
Monthly relative humidity	180,530 (MRH)	45,190 (MRH)	PRCP, TMAX, Solar, Wind, TMIN	-	-0.99	4.03
			PRCP, TMAX, Solar, TMIN	Wind	-0.52	4.13
			PRCP, TMAX, TMIN	Solar, Wind	-0.40	4.13
Relative humidity of the driest month	180,530 (MRH)	18810 (RHDM)	PRCP, TMAX, Solar, Wind, TMIN	-	-0.26	2.25
			PRCP, TMAX, Solar, TMIN	Wind	-0.76	4.93
			PRCP, TMAX, TMIN	Solar, Wind	-0.08	5.00

* Graphical structure and parameters. ** Proxy variables: Precipitation (PRCP), maximum temperature (TMAX), minimum temperature (TMIN), solar radiation (Solar), and wind speed (Wind).

Eskelson et al. reported similar RMSE values (3 to 4%) in a study in which they used air temperature in a set of linear models to estimate relative humidity in a Riparian forest (Eskelson et al., 2013), and Eccel reported RMSE values of 8–11% in his attempt to estimate relative humidity based on temperature and precipitation in the Italian Alps (Eccel, 2012). When comparing the performance metrics to the error of observation inherent in measurements using hygrometers, this study's accuracy falls in the middle of the accepted error range (1 to 5%) set for sensors (Eskelson et al., 2013; Harrison, 2014). Even though our metrics are thus similar to the ones reported by other authors, our approach has the additional advantage that it is possible to use new available information on proxy variables to update the states of the unknown proxy variables and therefore the target variable relative humidity Table 8 and Figure 15. Scatter plot of model-estimated vs. reported values of monthly relative humidity (MRH) and relative humidity of the driest month (RHDM) using complete and incomplete data. Wind: wind speed, and Solar: solar radiation. Data source: reanalysis dataset CFSR (Fuka et al., 2014; Saha et al., 2010).). This feature is relevant to real world situations, where missing information is a frequent condition. In the case presented in Figure 14B, the new evidence of PRCP, TMAX and TMIN provoked the update of the states of the (unknown) variables Solar, Wind and relative humidity (see Figure 14: compare the probability distribution of variables in Figure A,B).

Finally, we present a spatial comparison of model-estimated vs. reanalysis-reported RHDM values, and a suitability map of RHDM for coffee production over the region of Central America and Southern Mexico (Figure 16). It shows that the model reproduces the general spatial patterns well and coffee areas are located mainly in areas with high to medium RHDM-suitability. Thus, the relative humidity estimated with the method described in this study can be used reliably in spatially explicit land evaluation tools such as the model ALECA (Agroecological Land Evaluation for *Coffea arabica* L.), which consists of several climate, soil and landform variables that together describe and evaluate the suitability of land units for the production of Arabica coffees (Lara-Estrada et al., 2017).

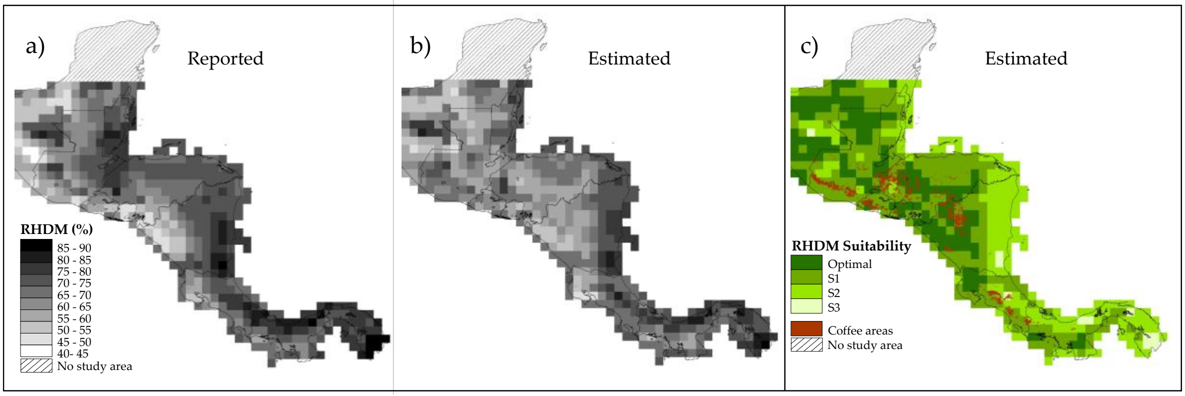


Figure 16. Maps of relative humidity of the driest month (A) reported in the CFSR reanalysis dataset for Central America and Southern of Mexico (pixel size 38 km × 38 km); and (B) estimated with our BN model. (C) Suitability map of relative humidity of the driest month for *Coffea arabica* L. based on the estimated values using complete dataset. Reference year: 2000. Suitability map modified from Descroik and Snoeck (2004): Optimal = Optimal conditions (50–60%), S1 = Very good (40–50% and 60–70%), S2 = Moderate (70–80%), S3 = Marginal (>80%).

Other potential areas of application for this method are in paleoclimatology, where missing information is a normal situation, in meteorology and climate science to predict and explore the dynamics between climate variables, or in crop modeling applications, where available datasets are frequently incomplete. In the future, we plan to include the use of Dynamic Bayesian Networks to estimate a variable's values at different time steps considering the previous state values and new information (Ghahramani, 1998; Ibargüengoytia et al., 2013).

4.3.3. Caveats

We used a complete dataset to create the model (structure and parameters); however, incomplete data is a common situation in the study area. Bayesian networks can deal with this situation by using learning algorithms for missing data, such as the Expectation-Maximization or Gradient Descent algorithms. Their implementation (in Netica) is similar to the steps described here using the Counting-Learning Algorithm (Korb and Nicholson, 2011; Norsys, 2015; Sucar, 2015b).

It should also be kept in mind that if the model is used in a different region, or with data of a higher resolution, variable states such as the range and maximum and minimum values need to be adjusted to the new conditions. In addition, in a high-resolution analysis, the addition of topographic and location (latitude and longitude) variables to the model may become necessary, as altitude, for example, can influence relative humidity at a local scale (Fries et al., 2012; Romps, 2014) and location could capture the spatial variability of the climate variables in the region. Further adjustments would also be necessary if the time step is changed from monthly to weekly or daily. Lastly, even though we built the model to estimate relative humidity, this method is equally suited for inferring missing values for other climate variables.

4.4. Conclusions

In this paper, we describe the application of a Bayesian network to generate missing data of relative humidity based on its relationship to proxy variables. The procedure is simple, requires a low modeling effort, and ensures that the relationships between all climatic variables remain consistent throughout the process. The model shows a good performance estimating relative humidity, even in cases of uncertainty when proxy variables are missing. We conclude that Bayesian networks are a suitable tool for estimating relative humidity for agricultural planning, an essential and less-explored domain for the application of probabilistic graphical models.

4.5. Appendices IV

Table A2. Summary statistics of relative humidity (RH), precipitation (PRCP), maximum temperature (TMAX), solar radiation (Solar), wind speed (Wind), and minimum temperature (TMIN) from the datasets MRH and RHDM. MRH: monthly relative humidity, and RHDM: relative humidity of the driest month.

Dataset	Variable	Unit	Mean	S.D.	Median	Minimum	Maximum	Skewness	Kurtosis
RHDM	RH	%	69.13	9.08	70.16	37.45	98.16	-0.41	-0.18
	PRCP	mm	1.05	1.79	0.47	0.00	24.41	4.19	24.69
	TMAX	°C	29.76	3.33	29.27	10.00	42.35	0.24	0.94
	Solar	MJ/m²	21.53	3.10	21.74	7.93	28.27	-0.39	-0.17
	Wind	m/s	3.37	1.73	2.85	0.77	11.51	1.08	0.64
	TMIN	°C	20.53	4.93	20.92	-2.66	29.17	-0.57	-0.26
MRH	RH	%	77.79	9.66	78.50	37.45	98.73	50.04	0.37
	PRCP	mm	8.13	8.38	5.47	0.00	83.94	-146.41	4.01
	TMAX	°C	28.75	3.05	28.48	10.00	42.35	-5.03	1.71
	Solar	MJ/m²	19.69	3.83	20.03	3.72	28.27	39.49	-0.04
	Wind	m/s	2.83	1.58	2.32	0.63	11.81	-109.93	1.35
	TMIN	°C	21.51	4.40	21.85	-2.66	29.54	50.07	-0.13

Data source: surface reanalysis dataset Climate Forecast System Reanalysis (CFSR) (Fuka et al., 2014; Saha et al., 2010).

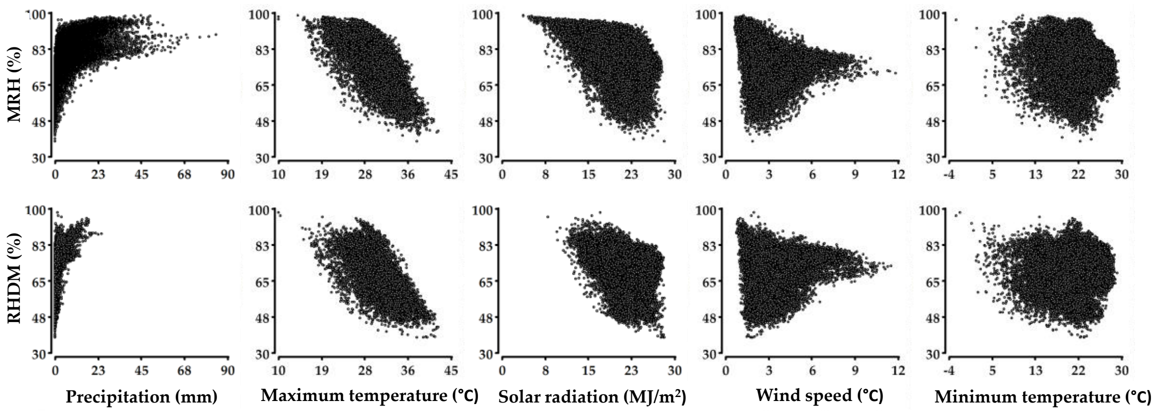


Figure A9. Scatter plots of variables monthly relative humidity (MRH), and relative humidity of the driest month (RHDM). Data source: surface reanalysis dataset Climate Forecast System Reanalysis (CFSR) (Fuka et al., 2014; Saha et al., 2010).

5. ESTIMATING THE REQUIRED SHADE LEVEL IN COFFEE PLANTATIONS

5.1. Introduction

The optimal mean air temperature for *Coffea arabica* L. is around 20 °C, and unsuitable values are below 10 °C and above 30 °C (Alégre, 1959; Camargo, 1985; DaMatta and Ramalho, 2006; Jaramillo and Guzmán, 1984; Larcher, 1981). These optimal and suboptimal values of air temperature have been integrated into the land suitability model to evaluate coffee areas; see Table 2 in Chapter 2 (Lara-Estrada et al., 2017). Considering that climate change scenarios for Central America describe a rise in temperature; farming practices that provoke a reduction in temperature such as agroforestry should be evaluated, improved and promoted (IPCC, 2014). In most of the coffee area in the region, coffee is already cultivated under shade in agroforestry systems. The services and goods provided by the trees are used by farmers to define their farming strategy; having as results a set of diverse coffee agroforestry systems respect to the composition and abundance of the trees species and input-intensification of the coffee component.

The coffee literature includes studies that indicate air temperature reductions due to the shade of trees (Barradas and Fanjul, 1986; Siles et al., 2010; Souza et al., 2012). But few studies modeled such cooling effect of trees (Lin and Lin, 2010; van Oijen et al., 2010); and no one has evaluated the shade as an adaptation strategy to face climate change for the coffee system in the region. Therefore, in this chapter, based on available survey datasets of coffee farms in Nicaragua and parameters from literature, we created a simple Bayesian Network model to estimate the required shade level. In the next chapter, we then use the shade model to explore the adaptation potential of shade under climate change conditions.

5.2. Usage of shading in coffee farms

The technical recommendations about the usage of shading such as tree species selection, pruning rates and shading levels considering altitudinal ranges, national coffee regions, and pest and disease management are done in some capacity by coffee extension services or agronomists in the Central America region (ANACAFE, 2018; Boudrot et al., 2016; ICAFE-CICAFE, 2011; IICA, 2004; López-Bravo et al., 2012). However inadequate shade usage [levels and pruning rates] has been pointed out in the region. Poor shade managementwas identified as one of the causes of the past coffee rust epidemic in the region (PROMECAFE, 2013).

In Nicaragua, coffee areas amount to about 190,000 Mz [approx. 133,500 ha] from which about the 96% of the coffee plantations is cultivated under shade conditions in agroforestry systems, and the main coffee areas are located in the Northern-central provinces of the country [Figure 17] (CATIE and MAGFOR, 2012). Therefore, we used three survey datasets to describe the use of shading in coffee farms in the Northern Central region of Nicaragua; then a new BN shade model is introduced, evaluated and used in the country's coffee areas.

Figure 17. Coffee areas [gray] by Provinces of Nicaragua (CATIE and MAGFOR, 2012).

The three studies are Altamirano (2011), Lara-Estrada (2005), and Vaast et al. (2003); their general information about the altitude range, shade levels, and provinces are displayed in Table 9. The location [coordinates] of coffee farms were available only in Altamirano (2011) and Lara-Estrada (2005).

Table 9. Datasets used to describe the shade usage by farmers in Nicaragua.

Study	n	Altitude (m.a.s.l.)	Shade (%)	Provinces
Lara-Estrada (2005)	67	630-1350	0-85	Matagalpa, Jinotega, Nueva Segovia, Madriz and RAAN
Vaast et al., (2003)	296	100-1500	10-80	Boaco, Carazo, Granada, Jinotega, Madriz, Managua, Masaya, Matagalpa, Nueva Segovia
Altamirano (2011)	404	785-1415	0-90	Jinotega

Vaast et al., (2003) was developed in the Project *Mejoramiento y Fortalecimiento en los Procesos de Certificación de Calidades y Comercialización del Café* [funded by European Union and UNICAFE]. Altamirano (2011) was funded by the Project *Apoyo a productores (as) de café en la Cuenca del Lago de Apanas* [funded by Coffee cluster of Jinotega and AECID].

We observed variations between the studies' reported shade values at the same altitudes [Figure 18]. Such variations may be a consequence of the difference in the method used to estimate the shade level: the shade was estimated by one person using a spherical densitometer in Lara-Estrada (2005); and by a team using the visual valuation method in Altamirano (2011) and Vaast et al., (2003). Therefore, given the implications of error of the latter method, we consider that dataset from Lara-Estrada (2005) provides a better approximation to the actual shade level (Bellow and Nair, 2003; Fiala et al., 2006).

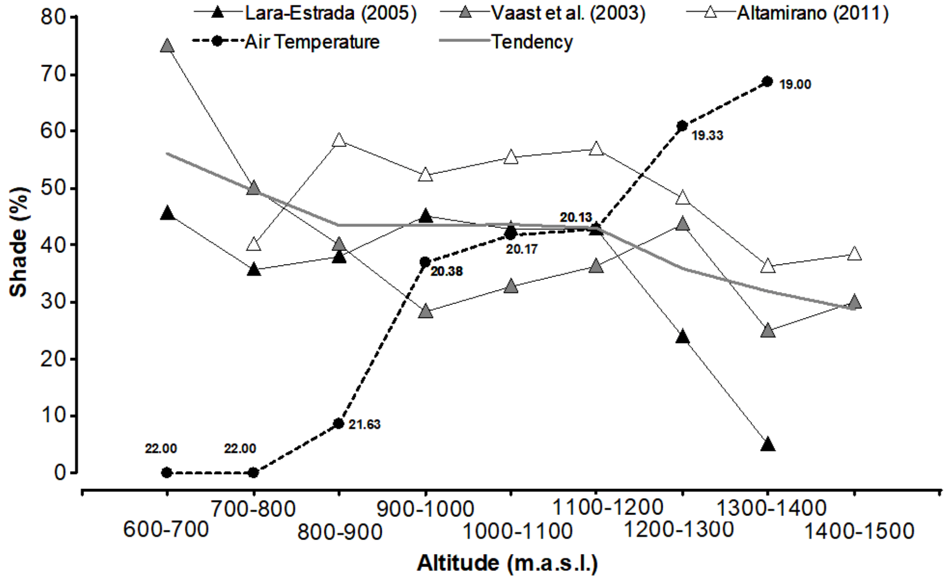


Figure 18. Reported shade values for coffee plantations at different elevations in Nicaragua. Shade values according to the data from Altamirano (2011), Lara-Estrada (2005) and Vaast et al., (2003). Tendency line indicates the average of the three datasets. Air temperature [°C] corresponds to the mean annual air temperature, which was extracted from the climate dataset Hijmans et al., (2005) and corresponds to the coffee plantations' location of Lara-Estrada (2005).

Despite the variations observed in the reported shade levels of the studies to a given altitude; the studies agree in describing a general tendency that depicts a negative relationship between shade and altitude, where shade levels increase along altitude decreases [warming conditions] [Figure 18], which means that farmers use higher shade levels at lower altitudes and lower shade at higher altitudes. Pearson coefficient results indicate a significant but low negative correlation for the datasets [Pearson correlation coefficient= Lara et al., of -0.25, Vaast et al., of -0.20 and Altamirano of -0.18]. The low coefficient may due to flat shade values [35-45 %] at 800-1200 m.a.s.l. [optimal and close to optimal air temperature values of 20 °C], see Figure 18.

The use of shade by farmer corresponds in a certain extent to the capacity of trees to alter the microclimate; particularly by reducing the temperature and increasing the relative humidity (Lin, 2008; Siles et al., 2010). Therefore, using a higher shade level is a known strategy for farmers to improve the stressing climatic conditions for coffee plants at lower altitudes. This microclimatic improvement might lead to an increase in coffee productivity [about 10-50%] and extend the coffee plantation longevity comparing with unshaded plantations at same conditions (Beer et al., 1998; Muschler, 2004; Vaast et al., 2016). Hence, shade trees add a layer of suitability to the environmental climate suitability [without shade] of the land making possible the coffee cultivation under certain levels of sub-optimal warming climatic conditions. The need for the cooling effect of the shading ends at altitudes that reach the optimal temperature values for coffee, and the use of shade under such conditions might induce yield reductions. Even though shade trees can under optimal or colder temperature conditions help to deal with other land limitations such as improving soil or protecting against windy conditions (Muschler, 2004).

The level of farming intensification is related to the level of shade used. Some farmers tend to use high levels of shade to reduce the photosynthetic activity in coffee plants, and therefore their demand for mineral fertilizers [, and avoid the corresponding associated costs] and extend the lifetime of the coffee plantation (Vaast et al., 2016). On the other hand, farmers with an input-intensive farming strategy tend to use the required or lower shade levels for higher coffee productivity; a third situation is related to those farmers that use inadequate shade levels that do not fit to their intensification level [i.e., high inputs under high shading or low inputs under low shading]. In Figure 19, using the dataset Lara-Estrada (2005), we identified the three situations by depicting the relationship between shade levels, fertilizer application rates, and coffee yields. Here, the decreasing of shade level across the altitude seems to be associated with a growing fertilizer application rate and the corresponding increment in yields, which agree with previous studies that found the coffee yield is very responsive to mineral fertilization (Meylan et al., 2013). However, we also observed that some farmers using a low-intensification farming strategy at lower altitudes [600-700 m.a.s.l.] used less shade than required at such altitudes. Therefore, the usage of shade in coffee farms depends on existing land suitability conditions but also on the farmers’ decision over the plantation; a decision that is influenced by socioeconomic and cultural factors (Lara-Estrada, 2005).

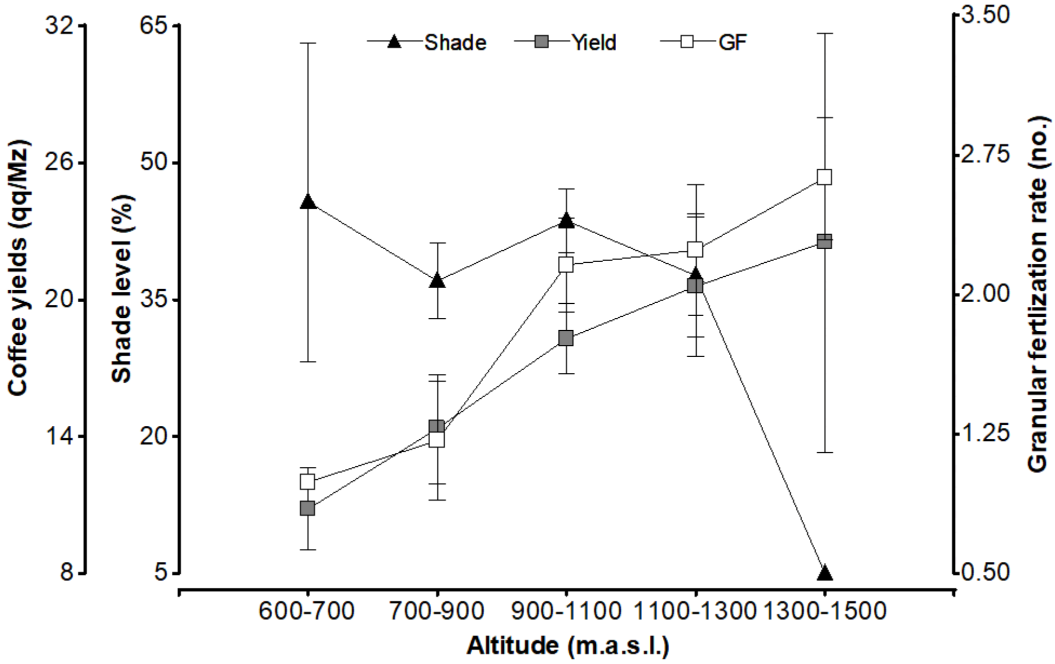


Figure 19. Shade levels (%), granular fertilizer rate usage (no.), and coffee yields [qq Mz^{-1}] at different altitudes. GF: Granular Fertilizers [Urea 46% and NPK]. The displayed values correspond to the mean and standard error. Dataset Lara-Estrada (2005). Notice the dynamic of change of the variables across the altitudes; e.g., 600-700 m.a.s.l. = high shading, low GF, low yield; 1300-1500 m.a.s.l. = low shading, high GF, high yield.

5.3. Modeling the cooling effect of shading

5.3.1. Model development

The ALECA's suitability function for air temperature [S] is a response curve that depicts the suitability level of a given air temperature value [0-100 %, where 100 is excellent] (Lara-Estrada et al., 2017). On the other hand, some studies report a reduction of temperature ranging from 1 to 5 °C as a cooling effect of the shading under agroforestry systems (Barradas and Fanjul, 1986; Fanjul et al., 1985; Garedew et al., 2017; Mariño et al., 2016; Morais et al., 2006; Righi et al., 2008; Siles et al., 2010; Souza et al., 2012). Therefore, based on this literature and the suitability function for air temperature of ALECA, empirical response functions were developed to estimate: 1) the shade level required (Sh_r) by coffee plantation given the environmental air temperature [T_i]; 2) the air temperature reduction due to shading [T_r]; and 3) the air temperature suitability under shading [S'] (Table 10).

Table 10. Functions to estimate the air temperature suitability with and without shading.

Variables	Equations
Shade level required (%)	$Sh_r = \begin{cases} 0, & if\ T_i \leq 20\ °C; \\ [(T_i - 20) \div 0.0444] + 0.023, & if\ T_i \leq 30\ °C; \\ 90, & Otherwise \end{cases}$ Where Sh_r is the shade level required (%) according to T_i. T_i is the annual mean air temperature (°C). T_i = 20 °C is assumed as 100% suitable, below this value shade is not required. If T_i > 30, the shade level is fixed to 90 %.
Temperature reduction (°C)	$T_r = 0.0444 * Sh_r - 0.023$ Where T_r is the mean air temperature reduction (°C) due to shading. Maximum T_r = 4 °C.
Suitability function for T_i under the shade of trees (%)	$S' = \begin{cases} S, & if\ T_i \leq 20\ °C; \\ T_i \sim N((\mu - T_r), \sigma^2\} \div T_\mu \sim (\mu, \sigma^2) \cdot 100; & if\ T_i \leq 30\ °C; \\ 0; otherwise \end{cases}$ Where S' is the suitability score (0-100 %, where 100% is excellent suitability) for a given annual mean temperature T_i considering the T_r under the Sh_r.
Suitability function for T_i under unshaded conditions (%)	$S = T_i \sim N(\mu, \sigma^2) \div T_\mu \sim (\mu, \sigma^2) \cdot 100$ Where S is the suitability score (0-100 %, where 100% is excellent suitability) for a given annual mean temperature in °C (T_i) that has a normal distribution with mean μ = T_μ= 20 and variance σ^2 = 3.89 (Lara-Estrada et al., 2017).

Based on the equations of Table 10, a Bayesian network model was created to infer the required shade by coffee plantations based on the environmental mean air temperature, and the corresponding suitability values for air temperature under shade and unshaded conditions.

Model structure. Using the Bayesian network software Netica (Norsys, 2018), a node was created for each variable; then, variables were linked according to the flow of input-output relationship described in the equations [Table 10]. Considering missing data is a common situation, and the air temperature values of a particular location might not be available for decision-makers, the variables Altitude [m.a.s.l.], and Provinces were added as proxy variables to infer the annual mean temperature [T_i]. Altitude has a negative correlation with temperature (Barry, 2008) and is commonly used as a proxy for climate suitability for coffee cultivation (Avelino et al., 2005; ICAFE-CICAFE, 2011; Pineda, 2001). Provinces represent the variations in latitude and longitude and landform (Barry, 2008; Linacre and Geerts, 2002; Taylor and Alfaro, 2005). The structural learning algorithm Tree Augmented Naïve Bayes [TAN] was implemented to define the links between T_i, altitude, and provinces; T_i was chosen as the target variable. The TAN algorithm adds the required links between variables to predict the target variable from data; and because of using Bayesian inference, the direction of links between two variables is irrelevant (Friedman et al., 1997; Norsys, 2018; Sucar, 2015c). Lara-Estrada et al. (2018) used the same approach to infer relative humidity using other climate variables as a proxy. The data of altitude *and* T_i were extracted from the Worldclim dataset at 1 km of spatial resolution for the coffee areas (Hijmans et al., 2005). The coffee map includes information on Provinces (CATIE and MAGFOR, 2012).

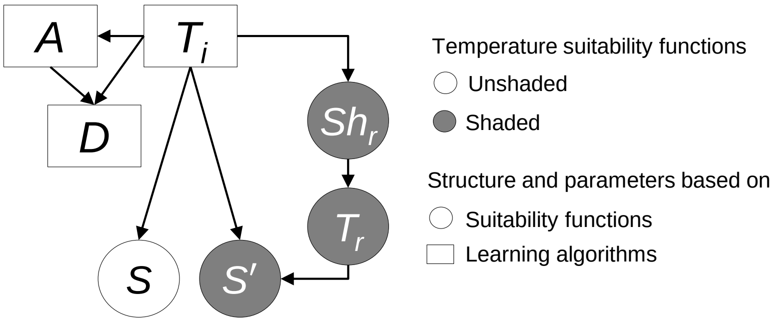


Figure 20. Shade model: estimation of the air temperature suitability for *Coffee arabica* L. under shaded and unshaded conditions. Unshaded condition [white circle]: T_i is the mean air temperature [°C] at full sun conditions, and S is the suitability score of T_i for coffee [0-100%, where 100% is excellent suitability] according to Lara-Estrada et al., (2017). Shaded condition [gray circle]: Sh_r is the shade level required [%] to a given T_i, the T_r is the air temperature reduction [°C] due to the cooling effect of the shade, and S' is the suitability score [0-100%] of T_i considering T_r. In case the T_i values are unknown, the altitude [A] and Provinces [D] can be used to estimate T_i. Parameters and structures for the variables in circles were defined using the functions in Table 10; variables in rectangles were learned from data using machine learning algorithms.

Variable discretization. First, the maximum and minimum for each variable were estimated. For required shade, temperature reduction and air temperature suitability with and without shade, the functions in Table 10 were used. In the case of altitude, provinces, and T_i, the values from the corresponding datasets were used (CATIE and MAGFOR, 2012; Hijmans et al., 2005). Then, an equal state size for each variable was determined, considering agronomical and practical factors (Marcot et al., 2006). For example, shade values less than 10% are similar to the error of measurement (Bellow and Nair, 2003), and difficult to track or implement in reality (by shade pruning). Therefore a range of 10 % was used as the breakpoint for shade. In the case of altitude, changes of 100 m depict the environmental lapse rate (Blandford et al., 2008; Hidalgo et al., 2017) and are used by the coffee practitioners to describe the land features (Descroix and Wintgens, 2004; ICAFE-CICAFE, 2011; Pineda, 2001).

Conditional probability relationships [parameters]. For variables with a built-in-function, the function was used to estimate each variable's conditional probability table using the feature "equation to table" in Netica (Norsys, 2018). For altitude, provinces, and T_i, the dataset created from Hijmans et al., (2005) and CATIE and MAGFOR (2012) were used to implement the Bayesian

Counting—Learning Algorithm and learn the conditional probability tables. This algorithm allows a variable to move from an initial ignorance [no parameters] to a set of conditional probabilities with their attached level of confidence [experience], based on the occurrence of each possible variable state in the dataset (Spiegelhalter et al., 1993). Once, all the parameters were learned by the model; it was compiled and ready to use [Figure 21A].

Model usage. Building the shade model in BN facilitate to us its integration to other BN models introduced in this document. Also, BN gives to users the opportunity to conduct inference considering data uncertainty, which we found particularly relevant for agricultural planning (Aguilera et al., 2011; Lara-Estrada et al., 2018; Uusitalo, 2007). So, we can enter as inputs data ranges, Gaussian distributions [mean ± standard deviation] or set of impossibilities for altitude or T_i or both to infer the Sh_r, S and S' (Lara-Estrada et al., 2017; Norsys, 2018). For example, if one enters the exact value of T_i of a given location [no uncertainty] to the model, the model is going to infer the rest of unknown variables [Figure 21B]. On the other hand, if one does not know the exact value of T_i, by entering to the model the approximate altitude range and provinces information, the model infers first the T_i and then the Sh_r, S and S' [Figure 21C].

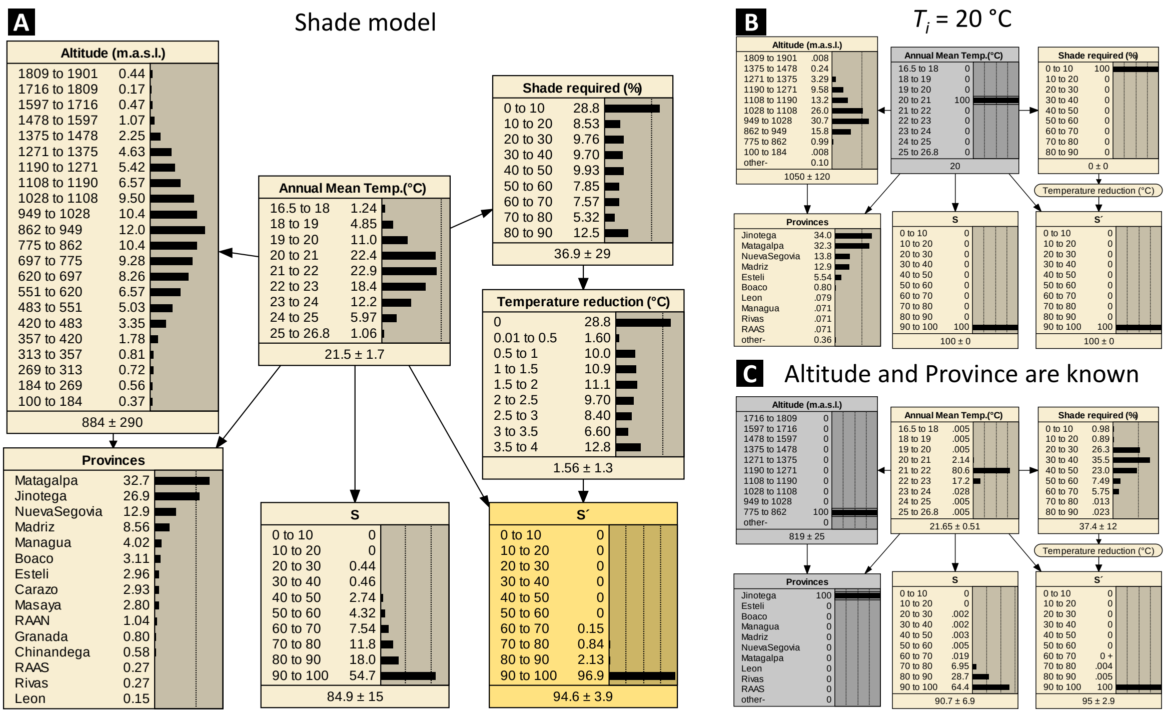


Figure 21. The shade model. A) Model compiled and ready to use; the displayed values indicated the prior values for the coffee regions in Nicaragua; Provinces indicates the share of coffee areas. Estimating the required shade and temperature suitability by entering B) temperature values and C) altitude and province data. S: temperature suitability under unshaded conditions [environment], and S’: temperature suitability under the canopy of trees [cooling effect of trees]. In B and C, temperature reduction and altitude were modified for visual purposes, but the functionality and variables states remain internally as A.

The model assumes that there is no need of shading at or less 20°C [100% environmental air suitability], and the maximum air temperature reduction is 4°C at 90% of shading. We acknowledge the model does not consider extensively the possible factors that influence the air temperature under shade conditions (Adams, 2010; Lin and Lin, 2010), but it considers the potential of the shade to reduce air temperature according to coffee literature for the region. As we will see, the model has very good performance inferring the shade level.

5.3.2. Model evaluation

We evaluated the model by testing its accuracy to predict the air temperature [T_i] from altitude and province information and identifying the variables have the higher influence over the inference of the required shade levels [Sh_r].

Inferring the T_i using altitude and province information: The spherical payoff metric was calculated to evaluate the model performance inferring T_i based on altitude and provinces information. The results indicate a spherical payoff of 0.8 [metric scores from 0 to 1, where 1 is the best performance] (Marcot, 2012; Norsys, 2018), which shows a very good model's performance considering the combined effect of latitude, longitude, and altitude inside a province (Adams, 2010).

The most influential variables over Sh_r. A sensitivity analysis using the Variance Reduction (VR) metric over Sh_r was conducted to identify the parent variables with the highest influence on it. The higher the VR score of X over Y, the higher the reduction of the variance in Y due to X (Marcot, 2012; Norsys, 2018). The results show the mean air temperature [T_i] as the variable with the highest VR [94%], then altitude [81%] and provinces [30%]. These ranking were expected since the Sh_r is calculated based on T_i, and T_i is more affected in the regions by altitudinal changes than provinces [low changes in latitude and longitude, see Figure 17]. However, the ranking reveals which variable should be prioritized for better inference of Sh_r.

5.3.3. Observed vs. inferred shade values

Based on the location of the actual coffee plantations [*Coffee arabica* L. var. Caturra] from the dataset of Lara-Estrada (2005), we used the shade model to infer the required shade level [Sh_r] and temperature suitability under unshaded and shaded conditions [S and S', respectively] [Figure 22]. The estimated shade corresponds to the *expected value*, which is the weighted mean value of the states [shade levels] per their probability of occurrence (Norsys, 2018).

The results from comparing the S and S' for coffee depicts the increase in air temperature suitability for coffee due to shading [Figure 22]. This supports the principle that shade trees add layers of suitability to the coffee lands, in our case to the air temperature suitability [microclimate]; and offers a clear illustration of the potential of shading as adaptation practice under climate change conditions (Vaast et al., 2016).

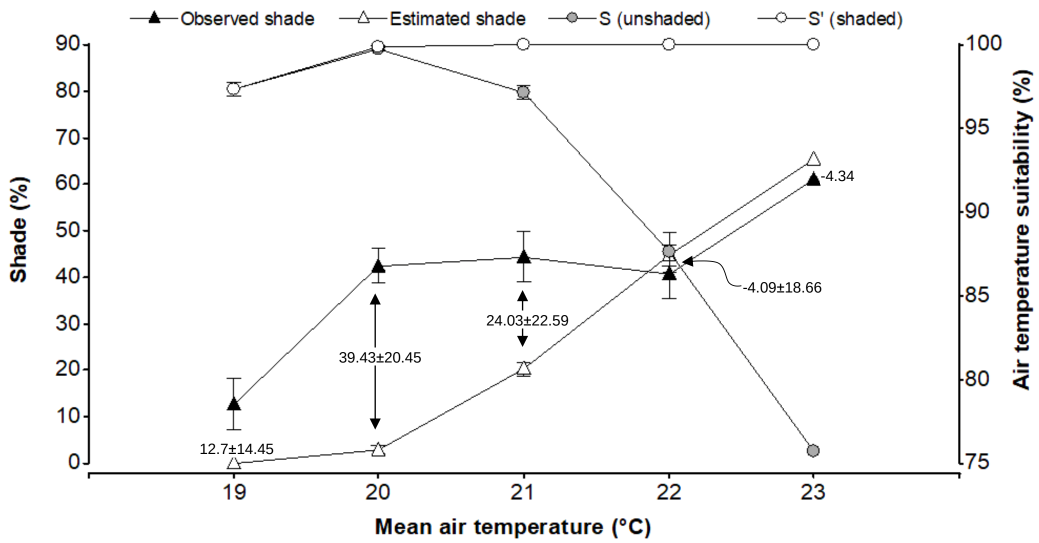


Figure 22. Observed and estimated shade levels, and the air temperature suitability with and without shade conditions [S′ and S, respectively]. Observed shade from Lara-Estrada (2005). Temperature values from Hijmans (2005) were used to estimate the S and S′. Optimal air temperature for *Coffea arabica* L. is 20 °C (Descroix and Snoeck, 2004). Error bars indicate standard error.

The comparison of the estimated and observed shade indicates a close agreement between their values at higher and lower air temperature conditions [$T_i \geq 22$ °C and $T_i \leq 19$ °C, respectively; whose corresponds to low and high altitudes, respectively] than under optimal ranges [19 °C > T_i < 22 °C]. Some farmers use higher shade levels than the coffee plantation requires at locations with optimal T_i [Figure 22]. As we addressed, these difference and pattern of shade usage are due to different biophysical and socioeconomic conditions of coffee farms [see Section 5.2]. Below the 22 °C, we did not observe coffee plantations using shade levels below the estimated shade values; and equal or above the 22 °C, the observed shade values are slightly higher [mean over shading < 5% shading]. In general, in both situations, coffee plantations use the required or over the required shade levels. So, in practice, the estimated shade defines the minimum shade level that farmers should use to compensate for warmer air temperature in coffee plantations under warmer conditions [Figure 22].

5.3.4. Required shade levels under climate change conditions in Nicaragua.

Using the location of the coffee areas in Nicaragua and the expected temperature under climate change scenarios RCP4.5 at 2050 [See Section 3.2], the future required shade level at 1 km resolution was estimated using the shade model. Also, we calculated the air temperature suitability under shade [S'] and without shade [S] conditions.

The results indicate the rising in temperature due to climate change will require an increment in the level of shade in coffee plantations. A generalized downgrade in the land suitability of coffee areas due to climate change is reported in Chapter 3 (Lara-Estrada et al., 2017). Under such conditions, adjustment in the shade level as a cooling strategy might play a key role as an adaptation strategy (Vaast et al., 2016). Here, our modeling results for the years 2000 and 2050 [RCP 4.5] confirm the need for such adjustments in the shading [Figure 23]. As the changes in the temperature are gradual, we can expect a gradual increase in the shading as well, from lighter to dense levels [Figure 23, Table 11]. In general, for the year 2000 about the 36% of coffee areas required shade levels equal or above 60%; the area that requires such shading increase almost doubles to 67% for 2050 [Table 11]. Considering the observed tendencies for over-shading by farmers here, in practice, we could expect even higher shade levels that we report for medium shade levels. However, if we track the changes in the required shading between the two periods, the changes are higher. Looking at the matrix of change of the required shade levels in Table 11, from the 100% of coffee areas that required a shade level between 0–10% in 2000, only the 21.11% of those area will still require shading of 0-10%, and the 78.89% of the coffee areas will require higher shade levels by 2050; for coffee areas with higher required shade levels the tendency is worse [Table 11]. These results imply that farmers may have to implement changes in the diversity and composition of the shade component, passing to a more dominated-woody trees typologies to reach such higher shade levels [See the related text to the Figure 25B].

Table 11. The matrix of changes of the required shade levels [Sh_r] in coffee areas under conditions of 2000 and 2050 [RCP 4.5] in Nicaragua.

Sh_r [%] 2000	2050 [RCP 4.5] 0 to 10	10 to 20	20 to 30	30 to 40	40 to 50	50 to 60	60 to 70	70 to 80	80 to 90	Total area [%, 2000]
Changes in this direction →										
0 to 10	**21.11***	7.13	19.17	28.24	20.42	3.46	0.48			22.14
10 to 20		**0.00**	0.31	7.10	51.23	32.10	8.64	0.62		4.96
20 to 30			**0.00**	1.39	11.98	42.53	37.50	5.03	1.56	8.83
30 to 40				**0.00**	1.64	8.74	53.01	32.42	4.19	8.41
40 to 50					**0.14**	1.70	16.17	48.23	33.76	10.80
50 to 60						**0.00**	1.33	14.58	84.09	8.09
60 to 70							**0.32**	1.42	98.26	9.70
70 to 80								**0.40**	99.60	7.65
80 to 90									**100.00**	19.41
Total area [%, 2050]	4.67	1.58	4.26	6.73	8.27	7.03	10.19	9.76	47.50	100.00

* 100% of the areas required the corresponding shade level in 2000, and the bold value indicates the remaining amount of area under the same correspond level by 2050.

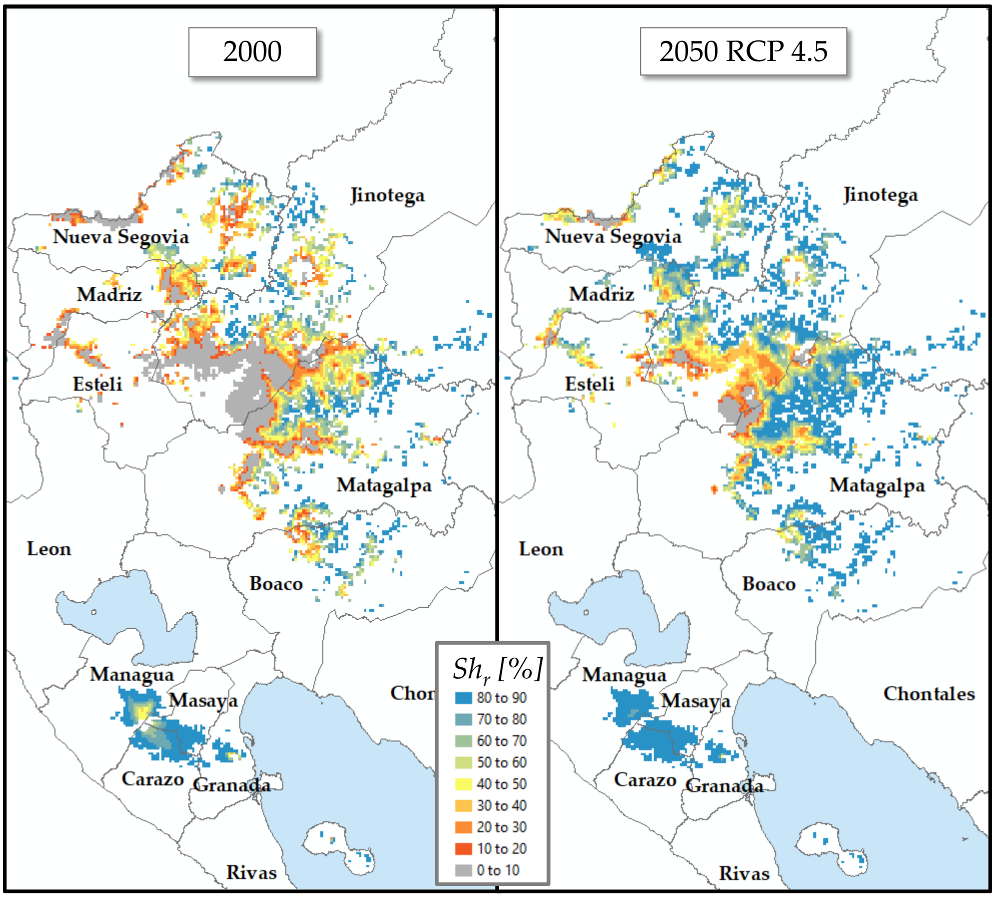


Figure 23. Required shade levels [Sh_r] of coffee areas for the years 2000 and 2050 [RCP 4.5] in Nicaragua.

Considering altitude, the required shade level will increase in average across the altitudinal ranges in the coffee areas by 23±14.76% in 2050 [Figure 24]. The highest increment [32 – 35%] in required shade occurs between 700 – 1100 m.a.s.l.; and for coffee areas with altitudes above 1100 m.a.s.l. that did not need shading in 2000; they will need in the future. The lower increment in the required shading at lower altitudes is because such areas already had high shade levels in 2000 [Figure 24B]. Hence, the margin to increase shading was small, and the cooling effect of shading was not enough to overcome the higher temperature; for this reason, the air temperature suitability under shading [S′] in 2050 is lower than in 2000 [Figure 24A].

Comparing the suitability of air temperature under shaded and unshaded conditions [S′ and S respectively], we observed an upgrade in the air temperature suitability under shading in both periods: about 17% more in 2000 and 31% in 2050. The higher upgrades occur at lower altitudes. Therefore, the microclimatic regulation service that shade trees provide to coffee plantations adds a layer of climate suitability to the existing conditions; allowing farmers cultivate coffee under less temperature suitable conditions. To the best of our knowledge, there are not similar results quantifying the benefits of the cooling effect of shade in coffee plantations in Nicaragua or Latin America. Our results support the statement that trees in agroforestry systems might play a relevant role as adaptation strategy under warming conditions. In the next chapters, we integrate these results in a broader analysis that considers the interaction between coffee productivity, adaptation, and mitigation to climate change.

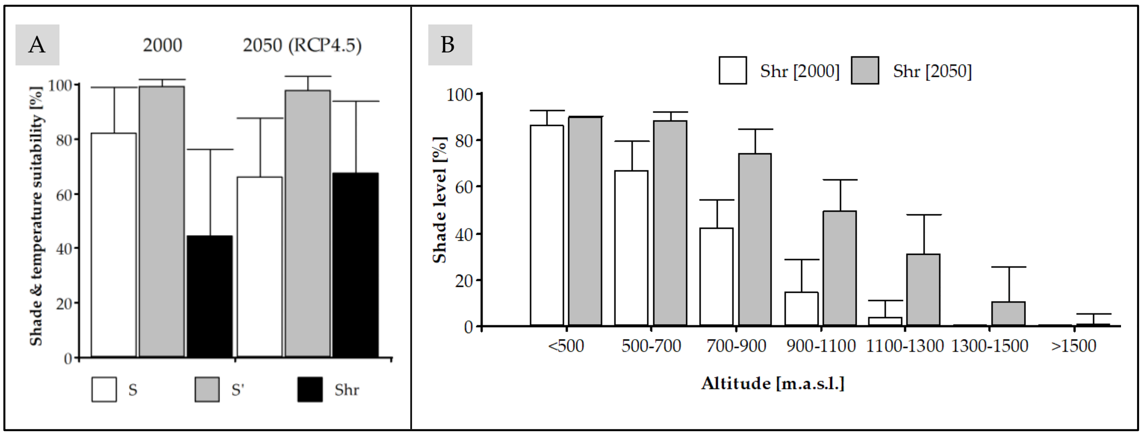


Figure 24. Required shade levels [Sh_r] and air temperature suitability without and with shade [S and S′, respectively] for coffee areas in Nicaragua. A) Average values for the country, B) Required shade levels in 2000 and 2050.

5.4. Conclusions

We introduced a new simple Bayesian network model to estimate the required shade in coffee plantations and evaluated the air temperature suitability for coffee with and without shade trees under uncertainty. From the comparison between observed and modeled shade values, we found the farmers tend to use higher shade levels than the required under optimal or close to optimal temperature conditions for coffee; and above and below the optimal range, the observed and modeled shade levels are similar. Therefore, in practice, the model defines the lower limit of the required shade level for coffee plantations.

The results show that in future required shade levels will have to increase on current coffee areas in Nicaragua. The coffee areas that require dense shading [≥ 60%] in 2000 will need to increase about the double by 2050. The upgrade in the air temperature suitability under shading conditions gave a first quantification of the potential of shade trees in agroforestry systems as an adaptation strategy under climate change. Finally, we provide results and a simple tool [shade model] with potential usage in the farm planning or policy-making processes.

6. A NEW COFFEE TYPOLOGY TO ADDRESS SYNERGIES AND TRADEOFFS BETWEEN PRODUCTIVITY, ADAPTATION AND MITIGATION TO CLIMATE CHANGE IN COFFEE AGROFORESTRY SYSTEMS

6.1. Introduction

Agriculture faces multiple challenges, such as soil degradation, water scarcity, and market crises. Climate change is another challenge, which can also aggravate existing ones due to the expected changes in temperature, precipitation variability and increasing occurrences of extreme events (Eakin et al., 2005; Matson et al., 1997; Tilman et al., 2002; Valenzuela, 2016). Climate change is expected to impact the climate suitability of land for coffee cultivation in coffee producing countries (Chapter 3, Karmalkar et al., 2011). However, agriculture is not only impacted by climate change; it also has the potential to alleviate or increase the severity of climate change as well by releasing or sequestering Greenhouse Gases (Smith et al., 2014; Tubiello et al., 2013). There are some agricultural systems like Coffee Agroforestry Systems [CAFS], with a high potential for crop adaptation and GHG mitigation to climate change (Matocha et al., 2012; Mbow et al., 2014a; Verchot et al., 2007).

In CAFS, the perennial component is composed of the trees and coffee plants, which are a standing carbon stock and source for the organic matter to the soil, and defines the mitigation potential (Defrenet et al., 2016; Schmitt-Harsh et al., 2012; Segura et al., 2006; Verchot, 2005). As an adaptation strategy, the CAFS improve the resilience and sustainability of farms by providing goods and services such as income diversification [e.g., timber, fruits], soil condition improvements [e.g., soil fertility, erosion], and microclimate regulation by cooling temperature under the canopy's trees [See Chapter 5] (Blanco and Aguilar, 2015; Camargo, 2010; Cerda et al., 2017; Lin, 2007; Vaast et al., 2015). However, the presence and intensity of those services for adaptation or mitigation fluctuate according to the arrangement of the CAFS' characteristics. These characteristics are related to the composition and structure of the perennial components and farming practices implemented, whose settings may provoke different levels of synergies and trade-off between coffee productivity, adaptation and mitigation objectives (Harvey et al., 2014). However, the current coffee typologies are focused on objectives related to biodiversity conservation [shade trees composition and structure] or agricultural intensification [low, medium and high inputs] (Haggar et al., 2011; Moguel and Toledo, 1999; Somarriba et al., 2004). So, we introduce new CAFS farming typology classification to address the synergies and tradeoffs between coffee productivity, the adaptation services, and carbon mitigation potential of CAFS under climate change.

6.2. Methods

6.2.1. Study area

The study area corresponds to the coffee areas in Nicaragua [Figure 25]. The cultivation of coffee *[Coffea arabica* L.] began in Nicaragua in the 19th century in the Provinces of Carazo and Masaya in the Pacific Region (Charlip, 2003; Diaz, 2001). Then, farmers located at medium and high altitudes [> 600 m.a.s.l.] in the Northern Central Region started its cultivation where currently is the most important coffee zone in the country. The country has about 183,161 Mz [126,586 ha] under *Coffea arabica* L. and 805 Mz under *Coffea canephora* [Robusta in South-east zone] (CATIE and MAGFOR, 2012); the total country production was about 2.02 million qq [91,800 t] in 2010 (ICO, 2015), and a farm's productivity was on average of 10.6 qq Mz^{-1}. About 96% of the national coffee plantations are under agroforestry systems (CATIE and MAGFOR, 2012). Central America expects to face a rising of temperature between 2 to 4 °C (Hidalgo et al., 2013; Karmalkar et al., 2011), and as we stated in Chapter 3, such changes represent a severe threat to coffee production.

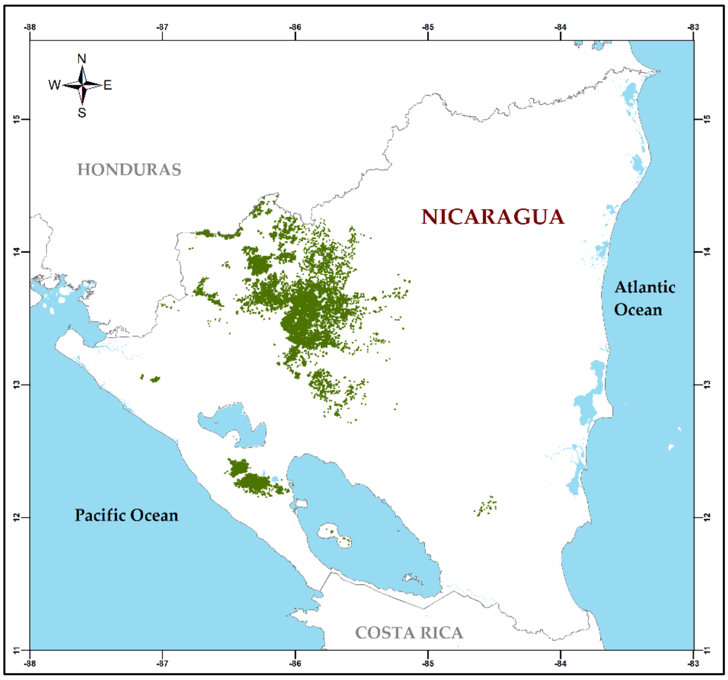


Figure 25. Map of coffee areas [green] of Nicaragua (CATIE and MAGFOR, 2012).

6.2.2. Data

We used the survey dataset of Lara-Estrada (2005) to develop the PAM-typologies. The dataset includes farming annual maintenance practices, coffee yields, coffee plant density, diversity and abundance of shade trees, shade levels, and others [Table 12]. Based on these variables and additional data raised in a survey], a new set of variables related to production cost and income, and carbon content were estimated for the surveyed farms from Lara-Estrada (2005).

Table 12. Surveyed variables from Lara-Estrada (2005) used in this study.

Category	Variable
Coffee plantation	Coordinates, altitude [m.a.s.l.]
Farming practices	Application rates of fertilizers, herbicides, insecticides, and fungicides. Rates of coffee and shade tree pruning, manual weed control, and cultural control of coffee berry borer.
Shade trees	Shade level [%], species richness [sampling plot (32 x 32 m), and tree density (trees Mz^{-1})]
Coffee	Yields [qq Mz^{-1}], plant density [plants Mz^{-1}], and age [years]

1 qq = 100 lb = 45.36 Kg. 1 Mz = 0.7026 ha.

Maintenance cost and net income. The annual maintenance cost [variable production cost] and net income for coffee and musaceas were calculated using the corresponding variables from the dataset, reference local market prices and production costs [Table 13 and Table 14]. Incomes from timber or fruits produced by trees were not considered (Somarriba, 1992). The cost and income data were obtained from agronomists and other technical personnel of institutions related to the coffee production in Nicaragua [Table 13 and Table 14].

Table 13. Equations utilized to estimate maintenance costs and net incomes.

Equations
Labor cost $$L = \sum a_i r_i c_i$$ Where L is the summation of the labor cost [US$ Mz^{-1}] of each farming practice [i] implemented, which are the product of the number of applications per practice [a_i], the man-day required per a given application [r_i] and the cost per man-day [c_i]. It used the average cost of man-day of US$ 6.04.
Inputs cost [agrochemicals] $$I = \sum a_i d_i ci_i + h$$ Where I is the summation of the input cost [US$ Mz^{-1}] of each farming practice [i] implemented – coffee and musaceas inputs cost [M_c], which are the product of the number of agrochemicals applications [a_i], the agrochemical amount required per application [d_i] and the cost of the input [ci_i], plus the harvesting and transport cost [h]. The d_i is the product of the crop plant density, the doses and cost of agrochemicals.
Musaceas cost $$M_c = m_b * m_c$$ Where M_c is the production cost [US$ Mz^{-1}], and is the product of the number of bunch produced [m_b] and the production cost per bunch [m_c].
Harvesting and transport $$h = y * ch$$ Where h_i is the harvesting [picking] and transport cost of the coffee harvested [US$ Mz^{-1}], which is the product of the yields [y] [qq Mz^{-1}] and the harvesting and transport cost [ch] [U$ qq^{-1}].
Maintenance cost $$M = L + I$$ Where M is the maintenance cost [US$ Mz^{-1}], which is the summation of the labor [L] and inputs costs [I].
Coffee income $$Ci = y * p_c$$ Where Ci is the coffee income [US$ Mz^{-1}] due to green coffee bean sales, which is the product of obtained yields [y] [qq Mz^{-1}] and coffee prices [p_c] [US$ qq^{-1}] in the local market. With the exception of the h, it assumed that the cost related to the coffee commercialization are included in the price (taxes and other services]. The coffee price was 114 US$ qq^{-1} corresponding to the average price paid to coffee producers in 2017 in Central America (ICO, 2018)
Musaceas income $$Mi = m_b * p_m$$ Where Mi is the income [US$ Mz^{-1}] due to the musaceas commercialization [US$ Mz^{-1}], and is the product of the number of bunch produced [m_b] and the price per bunch at farm [p_m]. The price was 1.067 US$ bunch^{-1} [average price estimated from Garming et al., 2013]. A 1/3 of the total of musaceas [stems Mz^{-1}] were considered productive.
Total income $$TI = Ci + Mi$$ Where TI is the total income [US$ Mz^{-1}] resulting from the sales of coffee [Ci] and musaceas [Mi].
Net income [profit] $$NI = TI - M$$ Where NI is the net income [US$ Mz^{-1}] obtained from the difference of the total income [TI] and the maintenance cost [M].

1 qq = 100 lb = 45.36 Kg. 1 Mz = 0.7026 ha.

Table 14. Labor and inputs parameters used to estimate maintenance cost. Labor values indicate the required man-days (MD) to conduct farming practices.

Practices	Labor per application		Inputs cost per application				Comments
	Labor (MD Mz^{-1})	Source	Input costs: Cost	Input costs: source	Doses	Source	
Shade trees pruning	5	a, b					
Coffee pruning	3	c					Maintenance, rock 'n' roll, capping
Weed control	4	d					Manual
Berry borer control	2	c					*Pepena and graniteo*
Application Fungicides	2	a, b	US$ 11.50 l^{-1}	e	1 l mz^{-1}	a	
Application Herbicides	2.5	d	US$ 7.15 l^{-1}	e	2 l mz^{-1}	d	
Application Insecticides	2	a, b	US$ 14.83 l^{-1}	e	1 l mz^{-1}	a	
Fertilization: NKP	2.5	a	US$ 29.03 qq^{-1}	a	1 onz $plant^{-1}$	c	18-46-0
Fertilization: Urea	2.5	a	US$ 21.93 qq^{-1}	a	1 onz $plant^{-1}$	c	Urea 46 %
Fertilization: Foliar	2	b	US$ 4.83 l^{-1}	a	1.5 l mz^{-1}	c	
Compost	4	a	US$ 17.74 mz^{-1}	a	1 applic. mz^{-1}	c	Ingredient cost
Harvesting	-	-	US$ 25.80 qq^{-1}	a			Picking & transport
Musaceas cost			US$ 0.425 $bunch^{-1}$	f			Includes labor

Sources: a = INTA, b = Personal communication with Raul Gutierrez [Coffee agronomist and farmer from Nicaragua], c = this study authors, d = Formunica S.A [Agrochemical company in Nicaragua], e = Personal communication with Walter Palma [Coffee agronomist from Nicaragua], f = according to Garming et al., (2013). It considered that 1/3 of the musaceas stems were productive during the year. 1 qq = 100 lb = 45.36 Kg. 1 onz = 28.35 g. 1 Mz = 0.7026 ha.

Carbon stock and fertilizer emissions. The perennial component is composed of the coffee plants and the shade trees in the coffee agroforestry systems. Musaceas [*Musa* spp.] are frequently found as temporary or permanent shade in coffee plantations in the Central American region (Garming et al., 2013; Staver et al., 2013). Even musaceas are not a real tree, they are considered as such in agroforestry because they provide services to the coffee plantation such as shading, wind protection, organic matter, and goods to farmers as a source of food and incomes (Alves et al., 2015; Moguel and Toledo, 1999; Somarriba et al., 2004). However, the musaceas' carbon storage capacity is much lower than woody trees (Somarriba et al., 2013). Hence, to capture the shading and carbon sequestration potential of the shade tree component, it was divided into woody trees and musaceas. The planting density of the shade trees [trees Mz^{-1}] was calculated from reported data in Lara-Estrada (2005). Allometric equations and shoot/root ratios were employed to estimate the above and below ground biomass of coffee plants and shade trees [Table 15]. Then, the carbon content per area [Mg C Mz^{-1}] was calculated using the corresponding planting density and conversion factors of biomass to carbon. For coffee and woody trees the default factor of 0.50 (IPCC et al., 2003), and for musaceas 0.488 (Kamusingize et al., 2017) were used.

Table 15. Equations used to estimate the carbon stock of coffee plants, woody trees, and musaceas.

Component	Component	Equation	R^2	Source
Coffee	AGB	$\log_{10} AGB = -1.181 + 1.991 * \log_{10} d_{0.15}$	0.93	Segura et al., (2006)
	BGB	$BGB = AGB * 0.9607$		Drefrenet et al., (2016)*
Woody trees	AGB	$\log_{10} AGB = -8.34 + 2.223 * \log_{10} dbh_{1.35}$	0.93	Segura et al., (2006)
	BGB	$BGB = Exp\,[-1.0587 + 0.8836 * \ln AGB]$	0.84	Cairns et al., (1997)
Bananas	ABGB	$ABGB = 0.0303 * dbh_{1.35}^{2.1345}$	0.99	Arifin (2001) cited by Hariah *et al.* (2001)

AGB: Above Ground Biomass, BGB: Below Ground Biomass, ABGB: Above and Below Ground Biomass, d_{15}: Diameter at 15 cm height, $dbh_{1.35}$: Diameter at breast height [1.35 m]. * the 0.9607 was estimated from the root biomass share [49%] of the coffee total biomass [55 Mg ha^{-1}] reported by Drefrenet et al., (2016). The diameter for coffee plants was $d_{0.15}$= 5 cm. In woody trees the $dbh_{1.35}$ = 26.49 cm for all the trees; the value was estimated from the reported tree diameters for shade coffee plantations in the dataset of the National Forest Inventory of Nicaragua (INAFOR, 2009).

6.2.3. Creating the PAM-typologies

The coffee agroforestry systems [CAFS] are complex and dynamic (Perfecto et al., 2007; Stacy M Philpott et al., 2008), because of the historical, socio-economic and biophysical conditions in the former and current coffee areas (Samper, 1999). Such complexity has been described in typologies to address a particular aspect or feature of the coffee system; some typologies describe the input intensification level usage by farmers [low, medium and high], or the source and type of inputs [organic or conventional], or the composition and structure of the tree component [multistrate, polyculture, monoculture, etc.](Haggar et al., 2011; Moguel and Toledo, 1999; Somarriba et al., 2004). Therefore, we created a typology that captures the features of the coffee systems considering coffee **P**roductivity, **A**daptation to climate change, and **M**itigation [PAM] objectives; and help to discover the tradeoffs and synergies between coffee systems. In this study, we defined 1) productivity as the relation between the incomes generated for agricultural products and their production costs per unit of land; 2) adaptation as any practice that improve the sustainability of the coffee production under climate change, which includes incomes diversification [e.g., sales from musaceas] and improve the cultivation conditions for the coffee plants [e.g., cooling effect of shading]; and 3) mitigation as the carbon content storage in the perennial components of the CAFS compare to unshaded crop systems. Therefore, and adaptation practice may reduce the coffee yields but maintain or increase the productivity of the land; and therefore, sustain the coffee producers (Haggar and Schepp, 2012; Verchot, 2005)

As the first step, the variables to depict the PAM features were selected. Based on literature and exploratory analysis [Pearson's correlation and principal component analysis, Table-A 3] the variables coffee yields [kg Mz^{-1}] and annual maintenance costs [US$ Mz^{-1}] for Productivity; the shade level [%] for Adaptation; and density of woody trees [trees Mz^{-1}] and musaceas [stems Mz^{-1}] for Mitigation were selected. The annual maintenance cost is a proxy for farming intensification [sum of annual labor and input costs]. The shade of trees is the adaptation practice evaluated in this study [cooling effect] and is also an essential practice in the farming strategy of coffee producers [See Chapter 5]. The planting density of woody trees and musaceas depicts the difference in carbon stock potential and shading of the tree component.

Second, using the selected variables a standard procedure to define farming typologies was conducted: a Principal Component Analysis [PCA] followed by hierarchical clustering analysis [Euclidean distance and Ward's method] was conducted to define the new typologies (Sarstedt and Mooi, 2014). As a result of the clustering analysis over the farms of Lara-Estrada's dataset, each farm was classified under one of the resulting typologies giving place to a new categorical variable "PAM-typology" in the dataset. An analysis of variance over the remaining variables was done using the PAM-typology as classification criteria to support the description of the typologies themselves (Salazar et al., 2018). The typologies were named, and their synergies and tradeoff to PAM described and discussed.

6.3. Results and Discussion

6.3.1. PAM-typologies

We identified five PAM-typologies using a PCA and clustering analysis [Figure 26]. The first three principal components [PC] explain 90.3% of the variability of the variables. The PCA gave a general description of the interaction between variables. High shade levels are more closely linked to high densities of woody trees than to high density of musaceas. Higher yields are strongly related to higher maintenance cost. We, also, observed a negative effect between shading and the yields and maintenance cost [Figure 26].

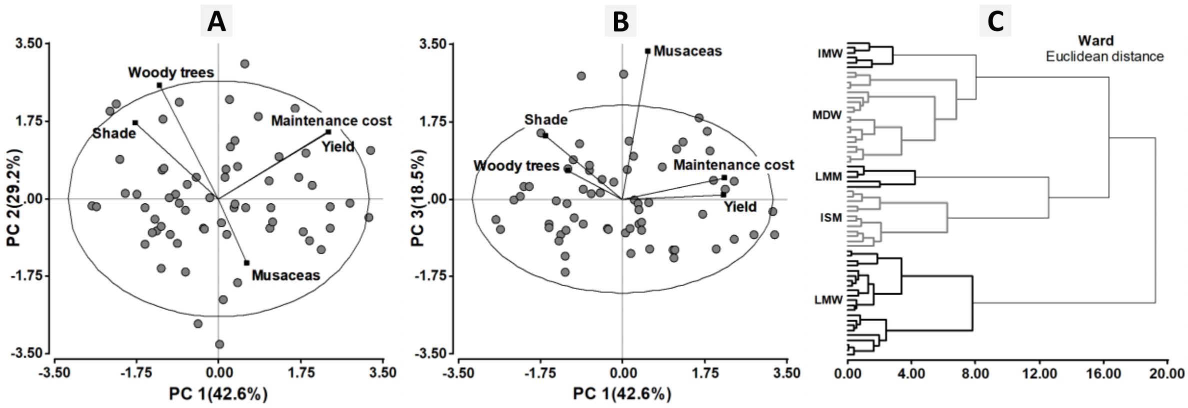


Figure 26. Principal component and cluster analysis conducted to obtain the PAM-typology. A) Principal components 1 and 2 [71.8%]. B) Principal components 1 and 3 [61.1%]. The three PC sum 90.3%. C) the clustering analysis that identified the 5 typologies: IMW = **I**ntensive management under **M**edium-dense shading of **W**oody trees; MDW = **M**edium-intensive management under **D**ense shading of **W**oody trees; LMM = **L**ow-intensive management under **M**edium-slight shading of **M**usaceas; ISM = **I**ntensive management under **S**light shading of **M**usaceas; LMW = **L**ow-intensive management under **M**edium-slight shading of **M**usaceas. Traditional, semi-intensive and intensive refer to the farming intensification level [annual crop maintenance: inputs and labor]. Musa and mixed shade refer to the type of shade trees predominant, being musaceas or musaceas + woody trees.

The typologies were named as 1) Intensive management under Medium-dense shade of Woody trees [IMW], 2) Intensive management under Slight shade of Musaceas [ISM], 3) Medium-intensive management under Dense shade of Woody trees [MDW], 4) Low-intensive management under Medium shade of Woody trees [LMW], and 5) Low intensive management under Medium-slight shade of Musaceas [LMM].

6.3.2. Synergies and tradeoff

The PAM-typologies are intended to capture and display the synergies and tradeoff of the coffee systems. Therefore, by describing the typologies and comparing them, we revealed their productive potential, as well for adaptation and mitigation to climate change.

Average values of biophysical and farming practices variables are displayed for each PAM-typologies in Table 16.

Table 16. Mean values for surveyed and estimated variables per PAM-Typology.

Variables	Units	PAM-Typologies				
		ISM	IMW	MDW	LMW	LMM
Altitude	m.a.s.l.	1092±173a	1007±61ab	1028±128a	923±171b	1024±254ab
Air temperature	°C	19.96±0.93c	20.15±0.35bc	20.56±0.67b	21.05±0.99a	20.08±1.19bc
Coffee yield	qq Mz^{-1}	30±50a	29±20a	17±50b	11±50c	7±20c
Shade	%	17±11d	51±7ab	55±17a	38±18bc	32±23c
Musaceas	Stems Mz^{-1}	164±121b	177±105b	109±98b	49±49c	408±143a
Woody trees	Trees Mz^{-1}	36±29c	145±49a	115±28a	72±43b	34±34c
Maintenance cost	US$ Mz^{-1}	1291±182b	1502±183a	879±180c	586±284d	566±127d
Tree spp. richness*	Spp. $plot^{-1}$	2.33±1.07b	5.33±2.80a	3.11±1.91b	3.64±2.40ab	3.60±2.44ab
Shade trees	Pruning rate	2.50±1.68b	3.83±2.40a	2.26±1.37b	1.09±0.61c	2.60±1.14ab
Coffee pruning**	Pruning rate	1.67±0.51a	0.50±0.55b	0.68±0.58b	0.50±0.51b	0.40±0.55b
Coffee plant	Plants Mz^{-1}	3455±535ab	3900±352a	3655±752a	3082±706b	2478±1096c
Granular fertilizer	Application rate	2.33±1.07b	3.83±1.60a	2.11±1.05b	1.36±1.43c	1±1c
Pesticides	Application rate	4±2.49a	4.83±2.48a	2.63±1.61b	2.45±2.22b	2±1.22b
Labor usage	MD Mz^{-1}	42±14b	56±8a	37±11b	28±14c	35±11bc
Input cost	US$ Mz^{-1}	1039±163a	1165±138a	655±160b	419±223c	355±110c
Musaceas income	US$ Mz^{-1}	91±23b	108±33b	76±36b	34±23c	206±73a
Net income	US$ Mz^{-1}	2214±490a	1856±232a	1077±495b	643±385c	412±336c
Carbon stock	Mg C Mz^{-1}	11±4c	26±6a	21±6b	14±6c	11±5c
Fertilizer emissions	$MgCO_2e$ Mz^{-1}	0.49±0.23b	1.05±0.52a	0.50±0.30b	0.23±0.26c	0.21±0.25c
LUC emissions	$MgCO_2e$ Mz^{-1}	40±13d	94±23a	77±22b	52±20c	40±20cd

Means with a common letter are not significantly different [p > 0.10] according to Fisher LSD test. The green color illustrates the rank of each typology for a particular variable. IMW = Intensive management under Medium-dense shading of Woody trees; ISM = Intensive management under Slight shading of Musaceas; MDW = Medium-intensive management under Dense shading of Woody trees; LMW = Low-intensive management under Medium-slight shading of Musaceas; LMM = Low-intensive management under Medium-slight shading of Musaceas. LUC emissions indicate the emissions in case of elimination of the coffee agroforestry system [Land Use Change]. Granular fertilizers: NPK and Urea. *plot = 1024 m^2. ** Maintenance pruning [sanitaria]. 1 qq = 100 lb = 45.36 Kg. 1 Mz = 0.7026 ha. DM = man-day.

The typologies are a mix of woody trees and musaceas; however, we use the terms "woody trees" or "musaceas" to indicate which of them is the most dominant considering the total tree density and carbon stock potential. Hence, it is possible the total dominance of one of them. Table 17 displays the proportion of coffee plantations using a given shading system [base on tree spp. composition and vertical structure] per PAM-typology. The shade systems represent the composition (dominant species] and structure [strata] of the three component in agroforestry systems (Somarriba et al., 2004). Except for *Inga spp.* [corresponding to ~17% of farms] and *Musaceas* [~12%], most of the shading systems combine musaceas and woody tree species. We found that a given shade system is implemented for some of the PAM-typologies; so, a given coffee plantation using a given shade typology could change to another PAM-typology by adjusting the composition of the perennial component, shading, and intensity of farming practices [Table 16 and Table 17].

Table 17. Agroforestry shade typologies in coffee plantations by PAM-typologies. The shade typologies reference the tree species composition and vertical structure [strata]*.

Shade typology	Survey [%]	Strata [no.]	PAM-typology [%]				
			ISM	IMW	MDW	LMW	LMM
Inga spp.	17.19	1	8.33	-	31.58	18.18	-
Remnant forest	6.25	2	-	33.33	-	9.09	-
Rustic	4.69	>3	-	16.67	-	9.09	-
Multistrata polyculture	6.25	>3	8.33	-	10.53	-	20.00
Inga spp. + Cordia + Musaceas	7.81	3	-	-	5.26	18.18	-
Inga spp. + Musaceas	40.63	2	25.00	33.33	52.63	45.45	20.00
Musaceas + tree spp.	4.69	2	16.67	16.67	-	-	-
Musaceas	12.50	1	41.67	-	-	-	60.00

* The shade typology classification is included in the survey dataset Lara-Estrada (2005), and was defined considering Somarriba et al., (2004).

Overall, the density of coffee plants and woody trees have a highly significant correlation to carbon stock [r = 0.36 and 0.98, respectively; Table-A 3]. So, the typologies dominated by woody trees IMW, MDW, and LMW have the highest carbon stock (Häger, 2012), and the woody trees component represent the highest carbon share of the total stock. In case of musaceas based-typologies ISM and LMM, the coffee plants represent similar or higher carbon content than the woody trees, and together sum more than 75% of the stock [Figure 27A], and only in LMM the musaceas reach the 25 % of the total carbon stock, otherwise remains equal or under 10% of the total stock [Figure 27B]. As we will explain next, there is a direct correlation between altitude, shade level, and carbon content.

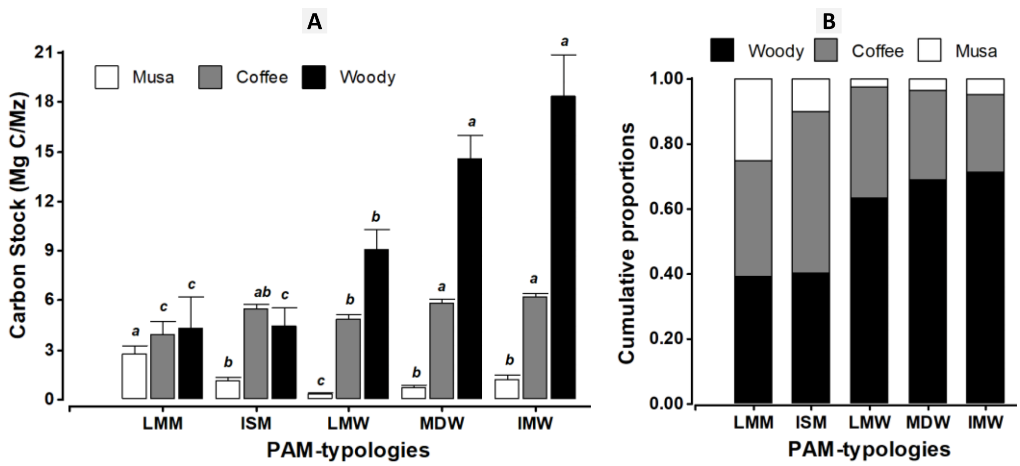


Figure 27. Carbon stock content by PAM-typology. A) Carbon stock values of coffee plants, musaceas and woody trees. B) Carbon stock share. Error bars indicate standard error. Means with a common letter are not significantly different [p > 0.10] according to the Fisher LSD test.

There is a negative correlation between the shade level and altitude. At lower altitudes, farmers use higher shade levels to alleviate warming conditions for coffee and consequently enhance the productive potential – see Chapter 5 (Muschler, 2004). Even though altitude and air temperature were excluded in the creation of the PAM-typologies, their effect was incorporated by the shade level and tree densities [Table 16 and Table-A 3]. Farmers tended to use the ISM at medium-higher altitude [19.96 ± 0.93 °C], the IMW and MDW at medium-lower altitude [20.15 ± 0.35 and 20.56 ± 0.67 °C, respectively], and LMW at a lower altitude [21.05 ± 0.99 °C]. In the case of LMM, it was found at different elevations [20.08 ± 1.19 °C] [Figure 28A]. Therefore, farmers that due to land suitability [air temperature suitability] or farming strategy reasons use a higher proportion of musaceas at higher altitudes or higher proportion woody trees at medium-lower altitudes [Figure 28B] indirectly provoke those coffee plantations at lower and medium altitudes have higher carbon stock and mitigation potential than those located at higher altitudes. In this sense, the carbon stock is a side result of the shade levels [adaptation] used by the farmers' farming strategy [productivity]; which in overall describes higher synergism between the three PAM-objectives in CAFS at medium-lower altitudes; and high synergism only for productivity and adaptation objectives but low for mitigation at higher altitudes.

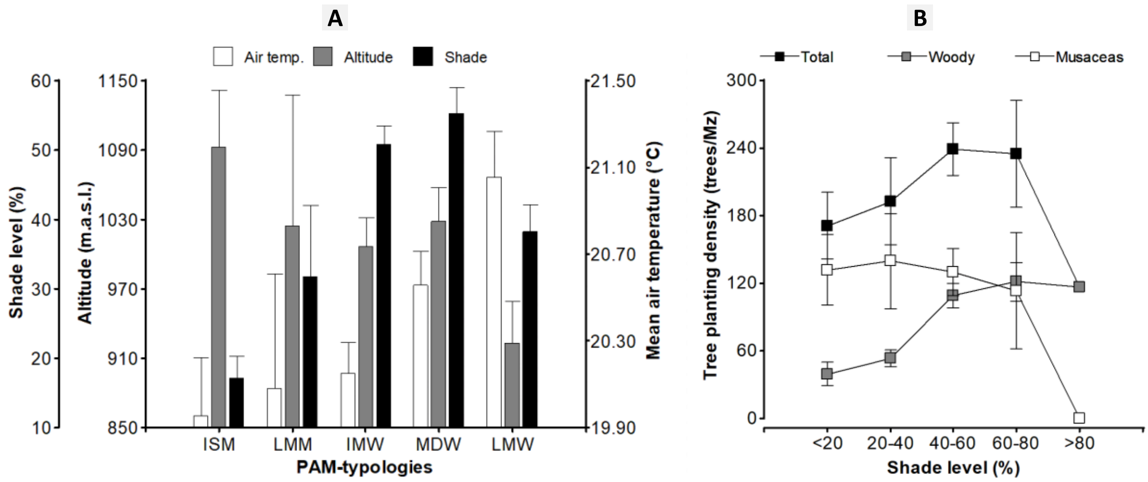


Figure 28. The interaction between shade levels, type of tree and altitude. A) Reported shade level, altitude and air temperature for the coffee plantations per PAM-typology. B) Trees density vs. shade levels: woody trees + musaceas = total planting density. Error bars indicate standard error.

There is a close interaction between shading as farming practice and farming intensification level: a tradeoff between adaptation and productivity – see Chapter 5. Like other studies, we observed a high correlation between farming intensification and coffee yields; the higher the intensification level [inputs and labor], the higher the coffee yields; where the external-inputs [agrochemicals] have the highest influence on yields and net incomes [Figure 29 and Figure 30]

(Castro-Tanzi et al., 2012; Meylan et al., 2013). Also, we observed a negative correlation between farming intensification and corresponding coffee yields with shading. For those PAM-typologies with medium and high farming intensification level, the shade seems diminishing the coffee yields: ISM and MDW have intermediate levels of labor and inputs usage, but the MDW's higher shade level declined its yields in comparison to ISM's lower shading and higher yields [Table 16]. Also, even the IMW have the highest farming intensification level; it have the same yields than ISM; IMW has medium-dense shading and ISM slight shading. In the case of the LMW and LMM, the low farming intensification level under medium-slight shading did not produce a rise in yields; so the limited usage of inputs and labor in farming practices [such as pest and diseases controls, fertilization rates, coffee pruning, and other] constrained the coffee yields [Figure 30]. Studies have reported this tradeoff between shading and yields (Beer et al., 1998; Haggar et al., 2011; Perfecto et al., 2005; Vaast et al., 2016). In an experiment in Nicaragua, Haggar et al. (2011) observed that under the medium and high intensification treatments the shading seems to "suppress" the effect of high inputs over the coffee yields. However, such yield reduction is compensated with an increase in the longevity of coffee plantation and lower inter-annual yield fluctuations (Beer et al., 1998; Vaast et al., 2016).

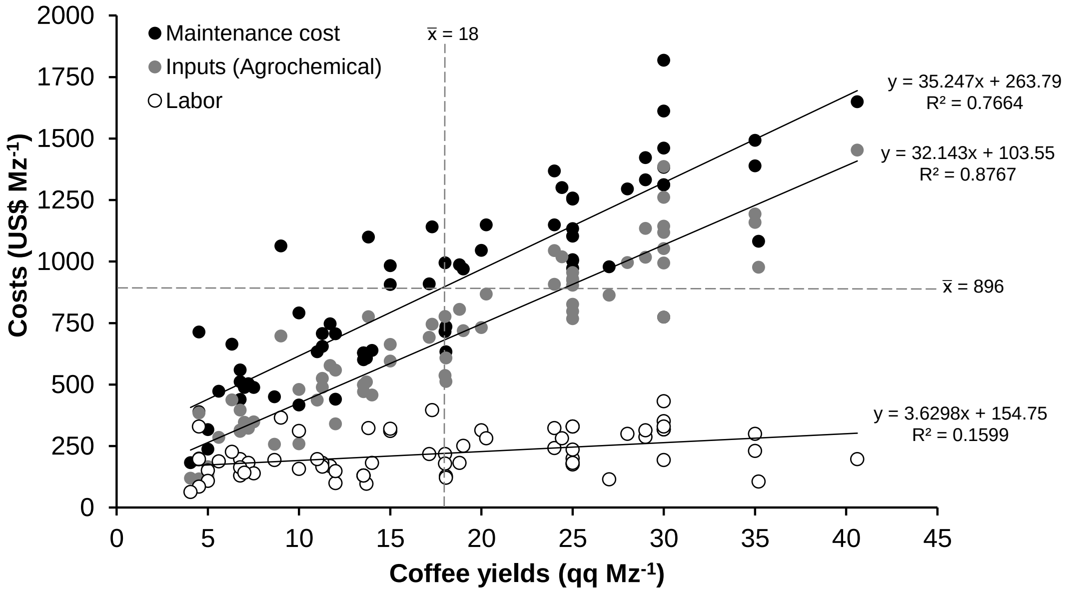


Figure 29. The interaction between maintenance cost [inputs and labor] and coffee yields. Dashed lines correspond to the mean values for coffee yields and annual maintenance cost.

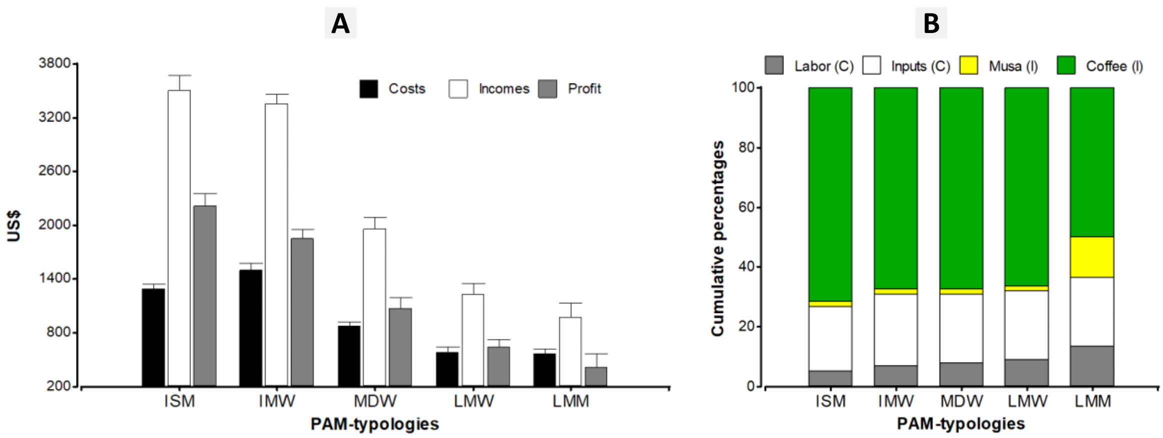


Figure 30. Production cost, incomes, and profit of PAM-typologies. A) Total maintenance cost [Costs], income [Incomes] and Profit from coffee and musaceas [profit = net income = incomes-cost]. B) Labor and external inputs [agrochemicals] cost [C], and the incomes [I] from coffee and musaceas sales.

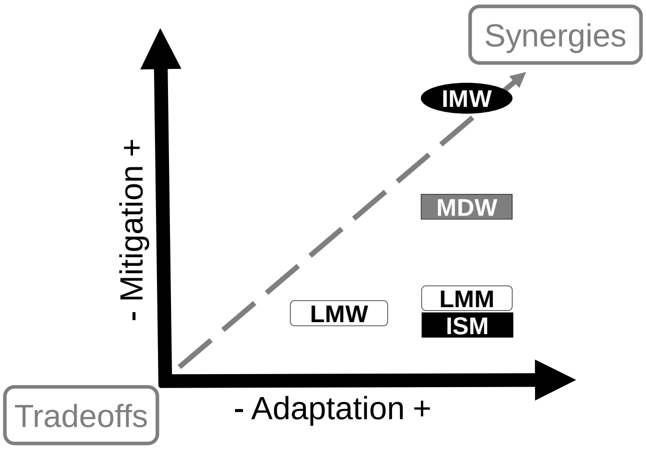
The required shade level can be reached under different proportions of musaceas and woody trees; higher shade levels are possible under the higher density of woody trees, and higher planting densities of woody trees produce higher carbon stock in the system [Figure 27]. Even if farmer required medium or dense shading at lower and medium altitudes [Figure 22]; we observed that many of them include musaceas as diversification and food security strategy (Albertin and Nair, 2004; Staver et al., 2013). On the other hand, at higher altitudes [with lower or optimal temperature] none or lower shading is required, typologies dominated by musaceas seems to be an option for some farmers under such conditions [Figure 28].

Financial stability, preference, and risk aversion are some of the main factors that influence a farmer' decision to implement a given farming practice (Babin, 2015; Kragt et al., 2017). Therefore, under market conditions of low coffee prices, the farmers' willingness to invest decrease (Babin, 2015; Meylan et al., 2017). They will adjust their farming practices [maintenance cost] to the expected prices [incomes]; this adjustment might imply reductions in the number of inputs and labor; and increasing the shade level to reduce the coffee plants' demand of nutrient (Beer et al., 1998; Vaast et al., 2016).

Even farmers can implement technical adjustments in the coffee system to increase the PAM-synergism, technical and financial support will be required in a farming planning setting to integrate such objectives the farming strategies of coffee producers; particularly, to promote mitigation practices [increase carbon stock or reduce the greenhouse gases emission]. The efforts to incentive farmers to implement mitigation practices using financial schemes have had low success in the agriculture, in part for the high transactional cost and conceptual constraints in practice (Siedenburg et al., 2012; Streck et al., 2012).

Coffee agroforestry systems with high tree species richness have a significant higher value for fauna and flora conservation than open sun or mono-shade systems (McNeely, 2004). Functional species, i.e., dispersers and pollinators, like bees and bats are beneficiated of the provision of food and shelter in such diverse shade tree systems (Jha and Vandermeer, 2010; Medina et al., 2007). In this study, the carbon content of woody trees was positively correlated to tree species richness [r=0.40, p=0.001]. So, systems with a high diversity of trees species tend to favor high carbon stock, which denotes synergism between mitigation and conservation objectives (Häger, 2012; Richards and Méndez, 2014). This is the case of the typologies IMW, LMW and LMM that report the highest number of species [Table 16].

Addressing the synergies and tradeoffs between the PAM objectives in the coffee agroforestry implies considering aspects that farmers evaluate to shape their farming strategies. So, in Figure 31, we created an idealized graphical representation to help to address the discussion over PAM objectives. In the figure, we assume the shading is the required shade level for the coffee plantation [which certainly might not be the case]; so, the adaptation axis refers to the intensity in the use of musaceas [planting density] as a diversification and food security strategy (Mbow et al., 2014b; Souza et al., 2010). The potential for biodiversity conservation is also included as the fourth objective. In general, the IMW typology displays the highest synergy considering the PAM and conservation objectives. Then, the ISM offers high synergy between productivity and adaptation objectives, but low for mitigation and conservation. However, as we discuss previously, some of the typologies are more frequent at given conditions than others; so, the land suitability conditions[climate and soil] might trigger the usage of certain farming practices according to the farmers' priorities at given locations.



Typology	Input level	Shade	Tree dominance
IMW	High	Medium-Dense	Woody trees
ISM	High	Slight	Musaceas
MDW	Medium	Dense	Woody trees
LMW	Low	Medium	Woody trees
LMM	Low	Medium	Musaceas

Figure 31. Graphical representation of synergies and tradeoffs between productivity, adaptation, and mitigation of the PAM-typologies. It assumed the required temperature reduction due to shading is optimal in each typology; so the adaptation axis represents the income of musaceas as a diversification strategy for climate change adaptation and food security. Tree spp. is a conservation indicator, the greater tree spp., the greater the potential for conservation.

6.4. Conclusions

The new typologies introduced in this study provide a pathway to address the synergies and tradeoffs between productivity, adaptation and mitigation objectives in coffee agroforestry systems. Each typology depicts particular biophysical conditions of the coffee plantation and socioeconomic situation of farmers; where land productivity and food security, and adaptation to climate change are the priority objectives that shape the farmers' farming strategy: typology (Lee, 2017; Mbow et al., 2014b). In this sense, the shade is a pivotal element in the interaction between productivity, adaptation and mitigation objectives. However the composition and abundance of shade trees are influenced by altitude; so, the typology dominated by woody trees IMW presented the highest synergies considering productivity, adaptation, and mitigation, and conservation at middle altitudes; and typologies dominated by musaceas present higher synergies considering only productivity and adaptation at higher altitudes. So, the potential of the coffee systems to reach higher synergism level between PAM objectives is conditioned for the land limitations and the technical response of farmers to deal with such limitations. In conclusion, The PAM-typologies can help farmers, agronomist and others decision-makers to define farming planning strategies or policies oriented to increase the resilience of coffee areas in Nicaragua.

6.5. Appendices VI

Table-A 3. Pearson’s correlation coefficient and significance values (only p < 0.1].

Coefficient\significance		A	B	C	D	E	F	G	H	I	J	K	L	M	N	Ñ	O	P	Q	R	S	T	U	V	W	X	Z
Altitude	A	1	0.000	0.059	0.024	0.057				0.050		0.099		0.029		0.011	0.049			0.061	0.059		0.026				
Air temperature	B	-0.89	1	0.012	0.002	0.023				0.065	0.059	0.090		0.011		0.000	0.006		0.035	0.012	0.010		0.006				
Coffee yield	C	0.23	-0.31	1	0.000	0.042							0.007	0.001	0.005	0.001	0.000		0.000	0.000	0.000		0.001				
Maintenance cost	D	0.28	-0.38	0.87	1	0.015					0.000	0.065	0.000	0.000	0.000	0.000	0.000		0.000	0.000	0.000		0.000				
Shade	E	-0.23	0.28	-0.25	-0.30	1	0.000			0.046		0.082			0.022	0.065	0.020		0.094	0.046	0.040	0.000		0.000			
Woody trees	F	-0.11	0.11	-0.09	-0.02	0.57	1	0.046		0.015		0.072										0.000		0.000	0.013	0.030	0.060
Musaceas	G	0.05	-0.19	-0.01	0.09	-0.09	-0.25	1	0.000		0.000	0.037						0.000							0.042	0.011	
Total tree density	H	0.01	-0.15	-0.05	0.08	0.15	0.17	0.91	1		0.000					0.052		0.000				0.024		0.018			
Tree spp. richness	I	-0.24	0.23	-0.13	-0.08	0.25	0.30	0.08	0.21	1												0.001		0.002			
Shade trees pruning	J	0.14	-0.23	0.20	0.44	-0.06	0.13	0.48	0.54	0.09	1	0.001		0.002		0.000	0.007	0.004			0.064	0.074	0.000	0.064			
Coffee pruning	K	0.20	-0.21	0.20	0.23	-0.21	-0.23	0.26	0.17	0.01	0.39	1				0.022					0.082						
Coffee plant density	L	-0.04	-0.01	0.33	0.44	-0.06	0.19	0.00	0.09	-0.01	0.20	0.11	1	0.048	0.012	0.017	0.000		0.042	0.006	0.006	0.003	0.001	0.003			
Granular fertilizer	M	0.27	-0.31	0.41	0.73	-0.17	0.06	-0.05	-0.03	-0.04	0.37	0.01	0.24	1	0.001	0.000	0.000		0.083	0.001	0.001		0.000				
Pesticides	N	0.01	-0.15	0.34	0.54	-0.28	0.04	-0.02	-0.01	-0.20	0.07	0.10	0.31	0.40	1	0.000	0.000		0.082	0.004	0.005		0.003			0.013	
Labor usage	Ñ	0.31	-0.42	0.40	0.72	-0.23	0.09	0.20	0.24	-0.09	0.71	0.28	0.29	0.68	0.53	1	0.000		0.080	0.001	0.001		0.000				
Input cost	O	0.24	-0.33	0.94	0.98	-0.28	-0.05	0.05	0.03	-0.09	0.33	0.19	0.43	0.67	0.48	0.59	1		0.000	0.000	0.000		0.000				
Musaceas income	P	0.06	-0.19	-0.11	0.00	0.08	-0.13	1.00	0.93	-0.01	0.41	0.23	-0.10	-0.06	-0.04	0.17	-0.04	1									
Net income	Q	0.19	-0.26	0.97	0.74	-0.21	-0.14	0.03	-0.03	-0.13	0.10	0.19	0.25	0.21	0.21	0.22	0.84	-0.08	1	0.000	0.000		0.084				
Coffee incomes	R	0.23	-0.31	1.00	0.88	-0.25	-0.09	-0.01	-0.04	-0.13	0.20	0.20	0.33	0.41	0.34	0.40	0.94	-0.11	0.97	1	0.000		0.001				
Total income	S	0.23	-0.32	1.00	0.88	-0.25	-0.11	0.05	0.01	-0.12	0.23	0.21	0.33	0.41	0.34	0.41	0.94	-0.05	0.97	1.00	1		0.001				
Carbon stock	T	-0.14	0.12	-0.11	0.04	0.49	0.98	-0.13	0.28	0.40	0.22	-0.14	0.36	0.11	0.09	0.15	-0.01	-0.01	-0.17	-0.10	-0.11	1	0.067	0.000	0.043	0.043	
Fertilizer emissions	U	0.27	-0.34	0.40	0.73	-0.11	0.16	0.09	0.16	0.02	0.53	0.07	0.41	0.91	0.36	0.73	0.65	0.05	0.21	0.40	0.41	0.23	1	0.079			
LUC emissions	V	-0.15	0.13	-0.11	0.04	0.50	0.98	-0.12	0.30	0.37	0.23	-0.15	0.36	0.09	0.11	0.16	-0.02	-0.01	-0.17	-0.11	-0.11	1.00	0.22	1	0.051	0.055	
Farm size	W	0.13	-0.18	0.12	0.03	0.16	0.31	-0.26	-0.13	-0.11	-0.15	-0.07	-0.01	-0.06	-0.04	-0.03	0.06	-0.21	0.14	0.13	0.11	0.25	-0.13	0.24	1	0.000	0.000
Coffee area size	X	0.04	-0.08	0.11	0.16	0.07	0.27	-0.32	-0.21	-0.19	-0.13	-0.11	0.10	0.18	0.30	0.17	0.16	-0.15	0.05	0.11	0.10	0.25	0.05	0.24	0.73	1	0.006
coffee age	Z	0.18	-0.14	-0.08	-0.13	0.05	0.24	-0.18	-0.09	0.05	0.00	0.15	-0.18	-0.03	-0.19	-0.11	-0.13	-0.16	-0.06	-0.08	-0.09	0.18	-0.12	0.17	0.42	0.33	1
		A	B	C	D	E	F	G	H	I	J	K	L	M	N	Ñ	O	P	Q	R	S	T	U	V	W	X	Z

7. EXPLORING THE SYNERGIES AND TRADEOFFS BETWEEN PRODUCTIVITY, ADAPTATION AND MITIGATION TO CLIMATE CHANGE OBJECTIVES IN COFFEE AGROFORESTRY SYSTEMS

7.1. Introduction

A common strategy to analysis coffee systems is classifying them according to some particular characteristics or objectives in farm typology systems; so, stakeholders can observe the differences and similarities between coffee systems and explore the impacts of given factors over the farms typologies (Haggar et al., 2011; Schnabel et al., 2017). Some farm typologies refer to the type of inputs used in the systems [convention and organic] or diversity and structure of shade component [polyculture, rustic, commercial, others] (Meylan et al., 2013; Moguel and Toledo, 1999; Somarriba et al., 2004). The description of each typology is commonly depicted using mean values obtained from a traditional quantitative or qualitative analysis (Salazar et al., 2018; Sarstedt and Mooi, 2014).

Climate change is a current concern for the coffee sector, particularly for coffee producer countries. Half of the optimal coffee areas will downgrade to moderate or marginal land suitability due to climate change in the Central American region by 2050 [Chapter 3]. Agroforestry has been identified and promoted as an adaptation option to alleviate the impacts of climate change; the shade of trees and goods improve the coffee plantation's microclimate, the income diversification, and food security [Chapter 5]; also, agroforestry has a high potential for carbon sequestration in their perennial component [trees and coffee plants](Mbow et al., 2014b; Verchot et al., 2007). However, the agroforestry coffee systems are diverse in composition and structure of the tree component, where the implemented shade levels respond to the local air temperature and farmer's strategy [Chapter 5].

The coffee farmers' farming strategy is defined considering their preferences, socioeconomic situations, the coffee plantation productive state, and land suitability conditions; as results of the interaction of these multiples factors the coffee agroforestry systems might experience a range of tradeoffs and synergies considering productivity, adaptation and mitigation objectives (Harvey et al., 2014). In Chapter 6, we introduced a new coffee typology system to depict the potential of agroforestry systems for Productivity, Adaptation and Mitigation to climate change [PAM] in

Nicaragua. So, we created a Bayesian network model based on the PAM-typologies to support the examination and selection of farming strategies [typologies] under current and climate change conditions.

7.2. Methods

7.2.1. Modeling the PAM-Typologies

Model structure. The variables that were used to create the PAM-typologies and the resulting PAM-typology were considered as "core variables" in the modeling; over which a second-layer of variables were added. For each of the core variables, a node was created, and the conditional dependencies portrayed as links were created from the dataset using the TAN algorithm [see Section 4.2.6](Friedman et al., 1997). Then, the discretization of each variable was obtained from a mean separation test using the PAM-typology as classification variable and the coffee yields, maintenance cost, shade levels, and density of woody trees and musaceas as dependent variables. Then, the middle distance between means was estimated to obtain the breakpoints between variables' states.

A second-layer of variables were added to the model to enhance the capability of the model to provide relevant information for decision-making. The second-layer variables were carbon stock [Mg C Mz^{-1}], net income [US$ Mz^{-1}], coffee plant density [plant Mz^{-1}], and tree richness [tree species $plot^{-1}$, plot sampling size: 1,024 m^2]. The carbon stock is an indicator of the CAFS' potential to mitigate CC (Schmitt-Harsh et al., 2012), and facilitate estimation of possible incomes from carbon markets (Atangana et al., 2014). The net income evaluates the productivity of the farming system. The coffee plant density provided agronomical information and is linked to yields and carbon content (Schmitt-Harsh et al., 2012; Toledo and Barros, 1999); and the species richness of the tree component is a proxy variable to describe the potential for biodiversity conservation of the system (Somarriba et al., 2004). The parents and discretization were defined for each one of these variables as follows. *Parents:* 1) The core variables and one of second-layer variable were added to a new modeling space, 2) then, the second-layer variable was selected as target, and the TAN algorithm implemented, and 3) a sensitivity analysis to findings using the variance reduction metric was conducted, and the resulting core variables with higher variance reduction scoring [and therefore the most influential] were selected as parent of the evaluated second-layer variable.

Discretization: an analysis of variance test was conducted for each new variable using as classification the variable that resulted in the most influential in the variance reduction metric.

Once the parents and discretization were defined for all the second-layer variables, one by one of the second layer variables were added to the core model and linked to their corresponding parent variables.

Finally, the conditional probabilities between variables [parameters] were learned using the machine learning Expectation-Maximization [EM] algorithm (Koller, 2009; Uusitalo, 2007), the model was compiled and ready to use. The structural and parameter learning were conducted using the updated dataset [see 6.2.3].

7.2.2. Model evaluation

Given the PAM-typologies were obtained from a standard PCA and hierarchical clustering analysis and the objective of the model is capturing and displaying the features of each PAM-typology in details, the model was evaluated by its ability to rightfully classify a farm in a PAM-typology. According to the Spherical Payoff metric, the model was able to successfully classify the farms. Scores rank from 0 to 1, where 1 is the best performance [Table 18] (Aguilera et al., 2011; Marcot, 2012; Norsys, 2018). The model also had an excellent score inferring the rest of variables, where most scored SP ≥ 0.92 [Table 18].

Table 18. Sensitivity analysis and spherical payoff results for variables of PAMO.

Variables		Sensitivity analysis[1]										Spherical
Read in this direction →		A	**B**	**C**	D	E	**F**	**G**	**H**	I	J	payoff
PAM-Typology*	A	-	41.40	38.00	34.40	25.70	24.80	20.90	20.00	18.70	4.23	1.00
Coffee yields	**B**	61.80	-	70.40	83.90	7.48	3.06	7.26	5.85	14.00	1.35	0.99
Maintenance cost	**C**	60.90	70.40	-	54.20	5.96	3.17	7.97	3.26	25.50	0.98	0.98
Net income	D	55.20	83.20	50.20	-	8.22	3.96	3.63	8.10	9.42	2.21	0.93
Carbon stock	E	45.80	4.15	5.80	11.20	-	78.10	6.72	26.40	6.18	5.54	0.97
Woody trees density	**F**	40.10	4.30	5.64	8.42	79.90	-	9.72	25.80	8.93	4.80	0.99
Musaceas density	**G**	32.80	3.09	3.08	0.70	3.81	13.80	-	2.89	9.26	0.03	0.89
Shade level	**H**	35.20	4.34	7.12	11.40	31.00	23.80	9.59	-	3.46	3.37	0.95
Coffee plant density	I	28.00	9.46	16.40	8.46	7.66	5.29	12.30	1.58	-	0.43	0.83
Richness (Tree spp.)	J	8.43	1.72	8.60	1.81	8.25	6.24	0.47	6.76	0.44	-	0.92

[1] The sensitivity analysis for continues variables was done using the metric variance reduction and for categorical variables the metric mutual information [entropy reduction] (Marcot, 2012; Norsys, 2018). In both metrics, the higher the value of X over Y, higher reduction of variance or uncertainty of X over Y. The spherical payoff metric evaluates the model performance to infer a given variable base on information from others variables [the scores go from 0-1, where 1 is the best]. * Categorical variable. Bolded variables are the selected core variables used to define the PAM-typologies.

A sensitivity analysis was run using mutual information method [entropy reduction] for the discrete variables, and variance reduction [VR] method for the continues (Aguilera et al., 2011;

Marcot, 2012; Norsys, 2018). The analysis revealed the degree of influence between variables [Table 18]. In both metrics, the higher the value of X over Y, the higher the reduction in variance or uncertainty of Y due to X (Marcot, 2012). The degree of influence of "X" variable over a "Y" is crucial to prioritize which input variables are essential to infer "Y." However, given the interconnection between variables, even variables with lower influence can improve the expected values. For example, if farmers want to select a PAM-typology, by entering the values of yields [VR=41.4], annual maintenance cost range [VR=38], and woody trees density [VR=24.80], the PAM typologies and others unknown variables in the model and their corresponding uncertainty are inferred. If also the shade level [VR=20] is entered as the fourth piece of evidence, the model infers and update the state values of all the unknown variables again, and the uncertainty attached to the inferred values is reduced; the more evidence is entered to the model the lower the uncertainty of the results.

We observed some resemblaces between the results of sensitivity analysis [VR or MI] and Pearson correlation coefficient values; however, the VR depicts the influence of a given variable's states changes over a target variable considering the prior probability distribution of the non-linear model, here in the PAM-model [continues and categorical variables]; and the Pearson correlation analysis evaluates the linear relationships between two continues variables (Hauke and Kossowski, 2011; Marcot, 2012; Norsys, 2018). Hence, the sensitivity analysis gives us a better assessment of the influence between the model variables that the correlation analysis.

7.2.3. What typologies have a higher potential for productivity and mitigation given required shade level?

As we discussed in Chapter 5, the shade of trees plays a pivotal role in coffee agroforestry systems by triggering or slowing down the biological and physical processes between the system's components, which have a direct impact on the PAM-objectives. Therefore, we used the PAM-model to depict in details the feature of PAM-typologies using the shade levels as a reference point in the analysis. We approached this using the following hypothetical situation and question: Supposing a coffee farmer organization knows the required shade level for coffee of a given plantation: What typologies have a higher potential for productivity and mitigation given required shade level? We answered this question by conducting the following query in the model: first, the required shade level was instantiated, then each of the PAM-typologies; for each combination of shade level and PAM-typology the expected values of net income and carbon stock was registered.

7.2.4. Selecting coffee farming strategies under multiple-objectives under climate change in Nicaragua

Coffee systems may have to experience adjustment in the intensity and type of farming practices under climate change conditions (Haggar and Schepp, 2012); changes in the shade levels are expected [See Chapter 5]. Also, there are efforts from different actors to promote and adopt farming strategies oriented to improve productivity, adaptation, and mitigation to climate change in the coffee systems; and scaling from climate-smart agriculture to climate smart-landscapes (Khatri-Chhetri et al., 2017; Scherr et al., 2012; Vaast et al., 2016). So, we used the PAM-model to run two hypothetical queries to identify farming strategies given multiples-objectives at different periods in coffee areas of Nicaragua: 1) in 2000, the farmers objective was to use the required shade level and maximize the net income of the coffee plantation; and 2) in 2050, the productivity, adaptation, and mitigation objectives were incorporated in the farming plans of coffee producers as a sustainable intensification strategy. In the first query, the objective is oriented to search the typology with the highest synergies between productivity and adaptation; mitigation is of marginal interest; in the second, the objective search for the typology with the highest synergy of the three PAM-objectives given the parameters entered and encoded in the model. The maximization consisted of the selection of the two highest state values of the net income [≥ 1466 US$ Mz^{-1}] and carbon stock [≥ 17 Mg C Mz^{-1}] to Productivity and Mitigation, respectively; then, it used the required shade values under the conditions at 2000 and 2050 [RCP 4.5] from for coffee areas in Nicaragua as Adaptation measure [Chapter 5]. The results of both queries were registered and compared.

As we mentioned, we explored what would be the most recommended PAM-typology given changes in a farming practice intensity and farmers' PAM-objectives between 2000 and 2050. This analysis is based on the assumption that the performance of a coffee system in a given location under future climate conditions occurs in coffee systems at different locations under current conditions. Therefore, some farmers are currently dealing with conditions that other farmers will experience under climate change conditions. We used the farming strategies of current farmers to infer farming strategies under similar future conditions. In this sense, we conducted an analogue analysis (Pugh et al., 2016). Also, we assumed that the PAM-typology depicts the existing coffee system in the country; no new adapted coffee varieties or other new adaptation practices were available.

The PAM-model captured the observed dependencies and interaction between its variables: farming practices [decision variables] and the outputs variables [yields, carbon stock, net incomes, and tree spp. richness] –See sections 5.2 and 6.3.2 (Beer et al., 1998; Vaast et al., 2016). Therefore, the model instead of simulating the biophysical processes in the coffee system's components interactions like process-based models do (van Oijen et al., 2010), it uses Bayesian inference based on the new evidence available and the encoded parameters [defined from observed data] in the model to infer and update the state of the unknown variables. For example, if a given coffee plantation required 40% of shading in 2000 and 60% in 2050, after entering the 60% of shade in the model, the model propagates such new evidence and infers the new state of each unknown variable according to the new evidence. In this sense, each PAM-typology depicts a particular combination of states and levels [intensity] of farming practices and outputs observed.

Given the nature and purpose of the PAM-model, the influence of the soil component is not directly incorporated in the model, but indirectly. We assume the soil conditions are incorporated indirectly in some model's variables and coffee areas themselves: 1) current coffee areas fulfill the minimum suitability soil conditions for coffee cultivation [Chapter 2], and 2) fertilization (nutrition plans) and shade usage complement each other to provide the required nutrition according to the coffee farmers' farming strategies [Figure 19, Figure 29 and Figure 30]. The fertilization and other farming practices that are related to competition for soil nutrients [like weed control] are incorporated in the model under cost management [Table 13 and Table 14]. Also, CAFS with a higher content of soil organic matter improves the physical and chemical soil properties. The soil organic matter is calculated from the below-ground biomass, which is estimated from the planting density of trees and coffee plants [Table 15].

7.3. Results and discussion

A Bayesian network model was created to explore and display the synergies and tradeoffs of PAM interactively in coffee agroforestry systems as a decision support system [Figure 32] (McCann et al., 2006; Pollino and Henderson, 2010). The model was made based on the PAM-typologies developed to address the synergies between PAM-objectives [Chapter 6]; however, using the PAM-Model, we obtained more details over the tradeoff and synergies between PAM objectives encoded in the typologies and explore multiples scenarios [See 7.3.1, 7.3.2 and 7.5 Appendices VII-B]. In this sense, the modeling enhanced the traditional typology approach to classify and describe agricultural systems.

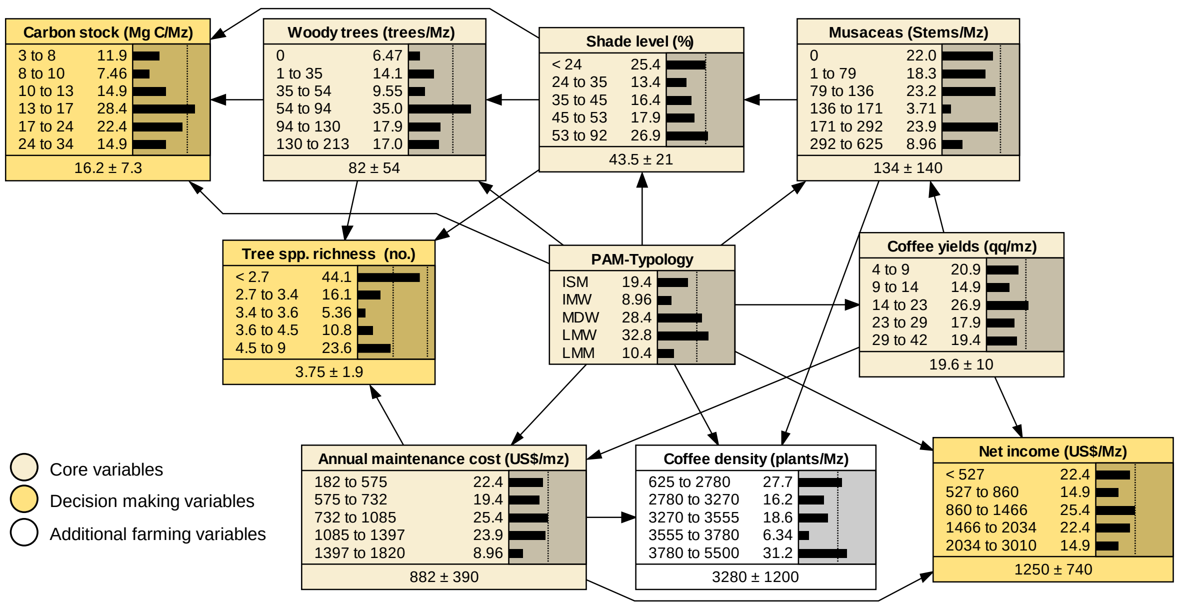


Figure 32. PAM-typology model. IMW = Intensive management under Medium-dense shading of Woody trees; MDW = Medium-intensive management under Dense shading of Woody trees; LMM = Low-intensive management under Medium-slight shading of Musaceas; ISM = Intensive management under Slight shading of Musaceas; LMW = Low-intensive management under Medium-slight shading of Musaceas.

In Chapter 6, a combination of PCA and hierarchical clustering analysis was used to define the typologies, which is a standard proceeding in the literature (Sarstedt and Mooi, 2014). Once the grouping was done, a mean separation test, descriptive statistic, and graphs were used to describe the typologies (Bhattarai et al., 2017; Meylan et al., 2013; Salazar et al., 2018). This approach is useful to give a general description but is constrained to general mean information. So, evolving the PAM-typologies into a model allows using Bayesian inference to explore how changes in the states of a variable influence others variables in a more intuitive and explicit manner. If one of the five typologies in the model is selected, an evidence propagation process occurs and due to the Bayesian inference and the conditional probability information of each variable the values of the unknown state of variables are inferred with a measure of uncertainty attached. For example, by selecting the typology IMW, in the case of coffee yields the inference resulted in a probability of 83.3 % that yields were in 29 to 42 qq Mz^{-1} and a probability of and 16.7% that yields were in 23 to 29 qq Mz^{-1}, and an expected value of 33.90 ± 5 [mean weighted value]. Also "if questions" in a forward or backward or both manner are possible using complete or missing information. Next, we show two applications of "if questions." These are desired features in agricultural planning or policy-making processes, where different scenarios or situations are considered and evaluated (McCann et al., 2006; Shibl et al., 2013).

7.3.1. What typologies have a higher potential for productivity and mitigation given a required shade level?

We framed this query using a hypothetical case where a coffee farmer organization plan to improve their coffee farmers' productivity considering adaptation and mitigation objectives. So, the organization stated the following question: What typologies have a higher potential for productivity and mitigation given a required shade level? Our results show that it is possible to obtain different potential for productivity and mitigation under the same shade level. For example, observing the shade levels of 35-45% under the different typologies in Figure 33, we can see a range of different outcomes over net income and carbon stock. The results indicate that for shade levels ≥ 35%, the IMW has the highest potential by showing the highest net income and carbon stock [Figure 33]. For lower shade levels [shade < 35%] the typologies MDW and ISM offer the highest potential. MDW has higher carbon stock than ISM, and ISM has higher net income than MDW at same shade levels. The LMW and LMM have higher tradeoffs: LMW has a medium to high potential for carbon mitigation but lowers net income, and LMM has a lower net income and carbon stock. Considering that the usage of a given shade level depends in practice on altitude [Chapter 5](Lara-Estrada, 2005; Muschler, 2001), the results suggest that IMW is the most suitable for medium and lower altitudes, and ISM for higher.

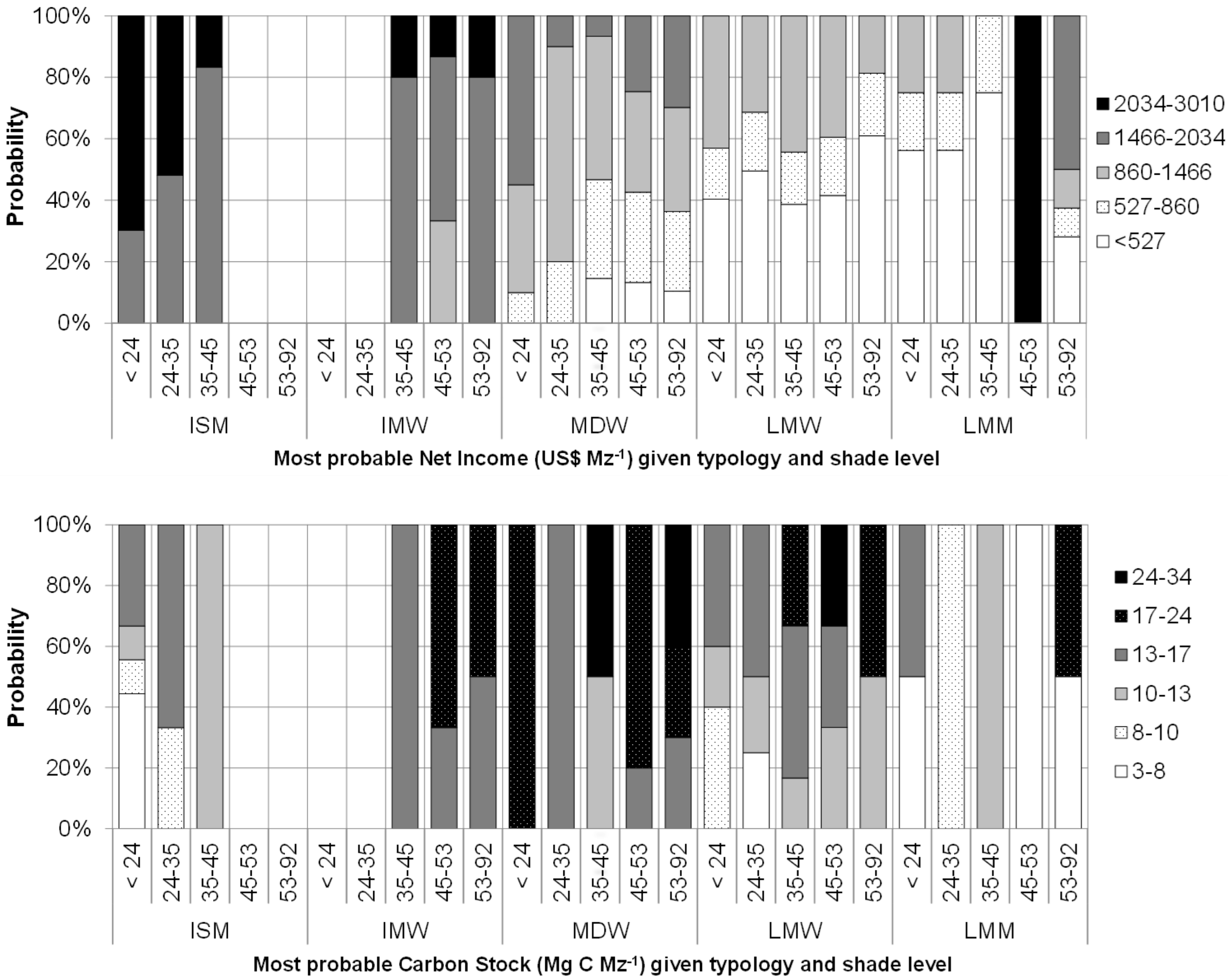


Figure 33. Net income and carbon stock for given shade levels per each typology. Values indicate the probability of the respective most probable states for net income and carbon stock. * These shade levels did not occur in that typologies; so, the model gives a uniform probability for unknown interactions. IMW = Intensive management under Medium-dense shading of Woody trees; MDW = Medium-intensive management under Dense shading of Woody trees; LMM = Low-intensive management under Medium-slight shading of Musaceas; ISM = Intensive management under Slight shading of Musaceas; LMW = Low-intensive management under Medium-slight shading of Musaceas.

By knowing which typologies have higher synergies to PAM or PA for a given shade level under climate change, farmers can evaluate which typologies are more suitable to their current coffee plantations conditions, risk perception, priorities, and preferences (Castellanos et al., 2013; Somarriba, 2009). A study conducted in the region over the risk perception of farmers over different coffee production stressors pointed out that even if farmers know what the problems and possible solutions are [adatation options], they might not implement the most promising but the option that better fit to their current situation and limitations (Tucker et al., 2010). So, instead of promoting the best alternative or farming strategy for a given condition, a set of possible alternatives like we show here might be more useful for the farmers and decision maker in the coffee sector.

7.3.2. Selecting farming strategies considering multiple-objectives under climate change conditions

Here we evaluated two queries, the first query corresponds to a scenario that maximize the net incomes and use the required shade level given the local temperatures in 2000; and the second query maximizes the net incomes and carbon stock given the required shade level according to temperature values under climate change in 2050. The IMW, ISM, and MDW were the PAM-typologies selected as recommended typologies for Nicaragua's coffee areas at 2000 and 2050. However, the proportional coffee areas for which they were recommended were different in both period [Figure 34]; ISM and MDW were the most dominant typologies in 2000, and MDW in 2050 [Figure 34]. These results indicate the most probable PAM-typology; however, it is possible to obtain a second or third probable PAM-typologies given the conditions, but for simplicity the focused over the most probable [Figure 32 and Figure 33]. The typologies LMW and LMM were not selected because their net incomes were lower than the queries conditions [Figure 33 and Table 16].

We did a tracking analysis of the changes between periods [Table 19], and the results show that the 100% and 55% of coffee areas which recommendation was IMW and ISM in 2000 changed to MDW in 2050; and about the 30% of ISM change to IMW by 2050. In essence, the changes in objectives [from PA to PAM] and conditions between 2000 and 2050 due to climate change led to changes in farming practices and therefore recommended PAM-typology.

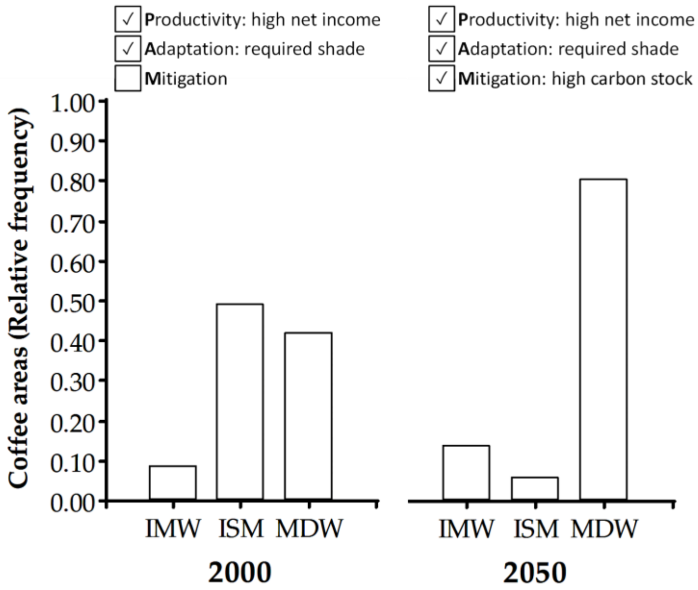


Figure 34. PAM-typologies for 2000 and 2050. IMW = Intensive management under Medium-dense shading of Woody trees; MDW = Medium-intensive management under Dense shading of Woody trees; and ISM = Intensive management under Slight shading of Musaceas.

Table 19. The changes of the recommended PAM-typologies for Nicaragua's coffee areas between 2000 and 2050.

Typology		Coffee areas [%] in 2050			Total
		IMW	ISM	MDW	
2000	IMW	0.00	0.00	7.09	7.09
	ISM	13.64	6.98	25.23	45.86
	MDW	0.00	0.00	47.05	47.05
Total		13.64	6.98	79.38	100.00

The changes in the recommended typology for a given coffee area between periods correspond to the changes in objectives and required shade levels due to climate change. The 2000-query assumed a scenario where farmers focus on obtaining the maximum possible net incomes and use the required shade levels [**P**roductivity and **A**daptation], and they are non-interested to mitigating climate change. Farmers focus their strategies in maintaining or increasing the profitability of coffee plantations, and are more concerned about other limiting factors that have affected their coffee production in past and recent years like international price crises and coffee rust epidemics (Avelino et al., 2015b; Bacon, 2005; Tucker et al., 2010). About shading, we used the required shade levels in this experiment, but in practice, this is not always the case. We discussed in Chapter 5 that farmers tend to use higher shade levels than required at altitudes with or close to the optimal temperature for coffee; which may due to a strategy to reduce the inputs levels in the plantations or (un)intentional mismanagement of the shade levels. One of the causes of the past coffee rust epidemic was the poor management of the shading in coffee plantations in Central America (PROMECAFE, 2013). In this study, we used shade level values calculated from air temperature [shade model from Chapter 5]; the changes in the local temperature of coffee areas are defined by the interaction between altitude, latitude, and longitude inside each evaluated period. Between periods, climate change becomes a new source of temperature variation [Table 5]. So, an increment in the required shade levels will be required under climate change conditions as an adaptation practice [Figure 24]. On average for the country coffee areas, an increment about 53% in the 2000-shade levels will be required by 2050 [Table 20]. This increment will require a gradual adjustment in the tree component of the coffee agroforestry systems [CAFS] between periods. Given higher shade levels were observed at a higher planting density of woody shade trees [Figure 28], a rise in the carbon content of CAFS is expected. According to our results, such rising indicates a national average carbon stock increment in CAFS about 50% in 2050 [Table 20]. Therefore, given the negative correlation between required shade and altitude [Chapter 5], we expect a similar relationship between carbon stock and altitude, where coffee plantations at lower altitudes [suboptimal conditions] may have a higher carbon stock due to higher shade levels, and vice-versa, under current and future conditions. Also, the increasing of the planting density of trees will be an opportunity for increasing tree species richness, which can improve the generation of services and goods for conservation and income diversification purposes (Moguel and Toledo, 1999; Somarriba et al., 2004).

Table 20. National average values of shade level, net income and carbon stock for coffee areas in Nicaragua.

Variable	Units	Mean (SD)	
		2000	2050
Shade	%	43.98(31.64)	67.52(26.07)
Net Income	US$ Mz^{-1}	1979.26(308.49)	1794.46(208.28)
Carbon Stock	Mg C Mz^{-1}	16.92(4.79)	25.3(4.55)

A net income reduction of 9.33 % is expected in overall for all coffee areas under climate change conditions [Table 20]. The net income was calculated based on current management cost (including harvesting) and incomes from sales of coffee and musaceas [when musaceas were presented in the plantation] –See 6.2.2. The ISM, IMW, and MDW are the typologies that have the highest expenditures in the annual maintenance cost, but also higher yields and net incomes. A reduction of less than 10% in net income may be lower if we consider those coffee areas will suffer a significant land suitability downgrade under the less severe climate change scenarios by 2050

[RCP 4.5]; where about 50% of coffee areas classified as excellent and very good land suitability might become moderate and marginal –See Chapter 3. However, this is possible due to in both of our queries the highest net incomes were selected as a condition; in our results the higher net incomes are associated with more intensive farming management [labor and input costs (agrochemicals)] that lead to higher yields [Table 16, Figure 29 and Figure 30]. Therefore, we might have a higher reduction in the incomes under less intensive management typologies like LMW and LMM; for example, Gay et al. (2006) using an econometric analysis reported a 34% of coffee production reduction in traditional rustic [similar to LMW] coffee systems due to climate change in a province in Mexico by 2020.

In the other hand, the use of the required shade level might compensate the warming conditions and reduce the land suitability downgrade due to climate change [Figure 24] but also promote the generation of others ecosystem services oriented to income diversification, mitigation, and even conservation purposes. In this sense, the queries consider multiples PAM-objectives under a sustainable intensification approach (Garnett et al., 2013; Pretty et al., 2011), where most probable PAM-typology depicts the farming strategy. Others efforts in sustainable intensification look to overcome some interactions that constrain the CAFS performance; use of adapted coffee varieties to shade conditions can improve the performance of coffee agroforestry systems (Bertrand et al., 2011; Lashermes et al., 2009) and fulfill and even surpass the income gaps describe here due to higher shade levels under climate change conditions.

If we consider the series of the recent challenges that the coffee sector have experienced (low coffee price crisis and coffee rust outbreak), and the 67% of the country's coffee farmers are small [less than 20 Mz], the queries may describe an optimistic scenario where farmers have the financial strength and technical support to invest in the requiered adjustment in their coffee plantations, which is not the case. Nicaraguan small coffee farmers are characterized for using a low level of agrochemicals, labor, and coffee planting densities, and have old plantations, and consequently low yields (IICA, 2003). Our scenario for 2050 considers a medium to high intensive farming management as results of the query of maximizing the net incomes; therefore, actual small farmers would have to increase their expenditures in their farming practices [inputs and labor] and even establishing new coffee plantations. The renovation of coffee plantations requires an investment that hardly can be assumed by small farmers without external financial and technical support (Avelino et al., 2015b). According to recent reports, the investment and support to coffee farmers have been minimum. The investment of the coffee industry in sustainability programs oriented to support and increase the resilience of coffee farmers is 0.035% of the yearly worldwide coffee industry value (Panhuysen and Pierrot, 2018).

Even though, there are some ongoing positive actions. Research institutions are implementing breeding programs to select and release new coffee varieties with diverse features that promise improving the performance of coffee plantations under future conditions (Bertrand et al., 2011; Lashermes et al., 2009; WCR, 2018). Such new varieties can be incorporated in the PAM-model to evaluate the impact of different strategies and conditions on the sustainability of coffee systems and the implications to reach the PAM and conservation objectives in a decision-making stage.

7.4. Conclusions

We introduced a new alternative to enhance the analysis of coffee systems by evolving traditional farm typology systems into a Bayesian modeling tool. The PAM-model captured the complex interaction between the components of coffee agroforestry system considering the original PAM-typologies. As a result, we obtain more comprehensive information on each PAM-typology's features and allow us to observe the possible impacts of changes in the farming strategies over the coffee system performance.

We explored the tradeoffs and synergies of coffee agroforestry systems considering productivity, adaptation, and mitigation to climate change objectives. We used an analogue modeling approach, where the performance of current coffee farms at temperature conditions that required similar shade levels than other location under future climate change conditions, to explore the effects of diverse objectives under a sustainable intensification strategy. Our results suggest that the expected adverse effects of climate change can be alleviated in some magnitude using and adjusting the current farming system [PAM-typologies] under a sustainable intensification strategy in the coffee areas in Nicaragua. Also, we believe that the typologies, PAM-model, and results of this study have a potential usage in planning and decision making processes where decision makers evaluate different strategies and practices.

7.5. Appendices VII

Appendix VII-A. Notes on the PAM-model

Discretization. The discretization of continuous variables is commonly identified as a limitation in BN modeling (Uusitalo, 2007); however, in the model, the discretized states are a favorable feature for better understanding and communication of the interaction between farming practices in a decision-making setting. Also, in the model's variables discretization, the states of variables were defined base on mean separation test that ensures the states have significant relevance considering the typologies.

Defined interaction. Although the described interactions between variables were in line with the literature, the model only infers interactions encoded in the dataset utilized; and for unknown interaction, the model provided uniform probabilities for the states of variables involved. However, if new information is available, it can be taught to the model adding new conditional relationships between variables or continue improving the existing ones (Norsys, 2018).

Missing components and variables. Some farming practices variables were not included to simplify the model (fertilization rates, pesticides usage, incomes from coffee and musaceas, others], but proxy variables were used instead. For example, labor and inputs cost of practices were used to estimate maintenance cost; so, maintenance cost represents the level of farming intensification. However, if more variables are required, they can be added to the model just like the case of coffee plants density.

Appendix VII-B. The "If questions" in PAM-model

In addition to the estimation of the PAM-typology given a set of farming practices, the PAM-model can deal with "If questions" in a forward or backward or both manners and using complete or missing information [Figure A-10]. For example, the model can be used to conduct the following if questions:

1) What would be the probable impacts over the coffee yields if the annual maintenance budget is reduced and the shade levels increased, or
2) Which farming practices produce the higher net incomes if the maintenance cost budget is reduced; or
3) What are the required planting densities of shade tree if a given shade level is required in a given PAM-typology.

Also, inside each typology, the user can explore some changes in the practices or explore what typology fit better to the required changes in the farming practices.

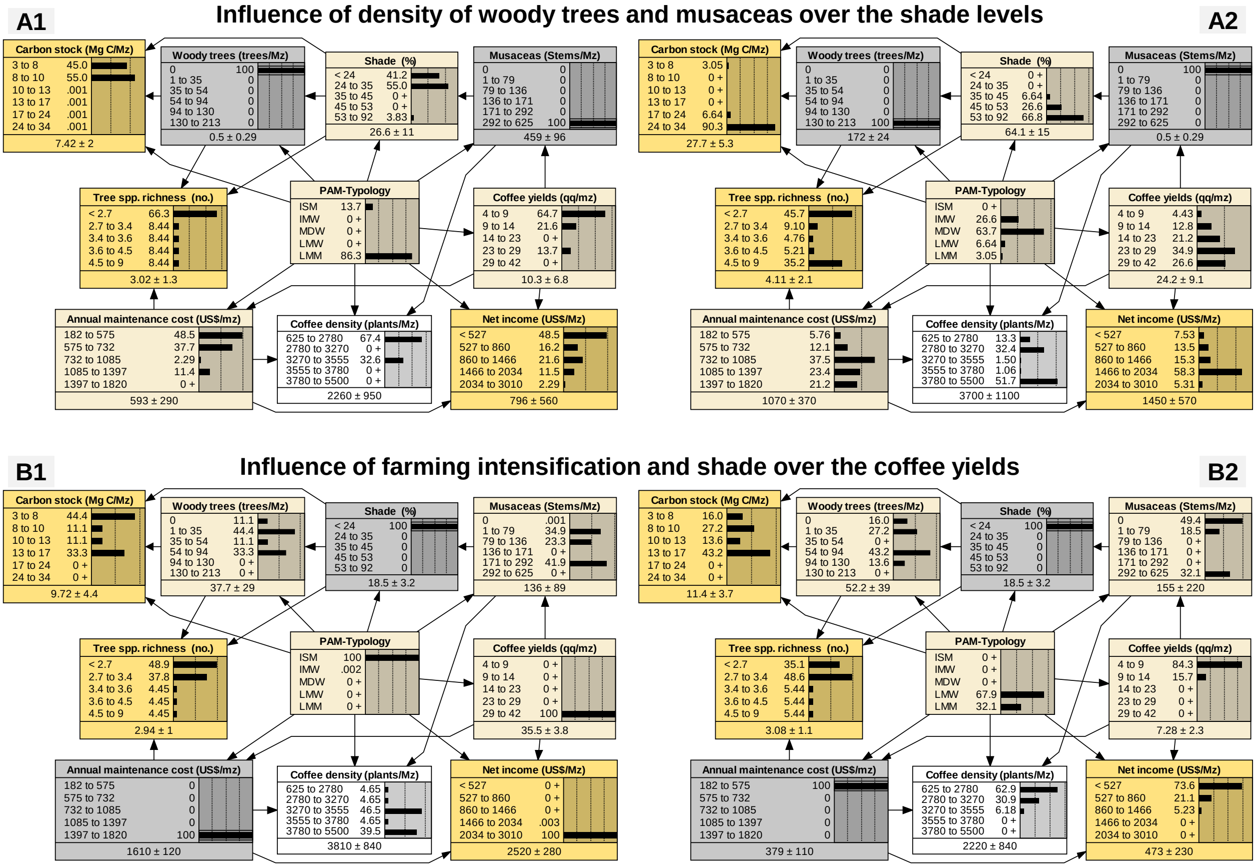


Figure A-10. Using the PAM-model to explore the interaction between farming practices and their impacts over the other variables. A) Influence of woody trees and musaceas density over shade level: A1) without woody trees and high density of musaceas; and A2) high density of woody trees and without musaceas. B) Influence of farming intensification and shade level over coffee yields. B1) the highest maintenance cost (high usage of inputs and labor] and lowest shade level; B2) the lowest maintenance cost and shade level. Notice the influence over the other model variables.

8. CONCLUSIONS

Agriculture is and will continue facing multiple threats that challenge its capacity to produce enough food and goods for a growing population. Decision-makers need information, knowledge, and the tools to evaluate potential damages and to find solutions to these threats. In this thesis, I explored the challenges and impacts that climate change represents to coffee production in Central America and evaluated the current coffee systems in terms of productivity and adaptation and mitigation potential to climate change. To do this, I conducted a series of studies that form part of an integrated framework of analysis that include 1) a land suitability evaluation under current and future conditions, 2) an evaluation of adaptation practices to climate change, and 3) the identification of potential tradeoff and synergies between productivity, adaptation and mitigation objectives in coffee agroforestry systems.

1) Land suitability evaluation under current and future conditions. Most of the coffee in Central America is cultivated in agroforestry systems. Agroforestry systems are highly complex and diverse in objectives, structure, and composition; such complexity constrains the use of process-based models beyond the plot level. At the regional level, land evaluation frameworks have been used to assess the suitability of particular pieces of land for crop production. I, therefore, developed the first land evaluation BN model for coffee, named Agroecological Land Evaluation for *Coffea arabica* L. (ALECA). The model is based on a new set of suitability functions developed from empirical data and a literature review [Chapter 2]. ALECA was then used to evaluate the impacts of climate change on land suitability for coffee production [Chapter 3]. Under the less severe climate change scenarios for 2050 [RCPs 2.6 and 4.5], approximately 50% of the area currently considered excellent or very good for coffee production will experience a downgrade to only moderate and marginal suitability and virtually disappear under the severe climate change scenario based on RCP 8.5. The downgrade in land suitability will negatively impact the coffee areas; so, adaptation actions need to be implemented in time to avoid a reduction in the productivity and quality of the coffee produced in the region.

2) Evaluation of adaptation practices to climate change. Agroforestry generates multiple services and goods for farmers and the environment. The regulation of the microclimate is a service that improves the local environmental conditions and therefore has a high potential to reduce the impact of climate change. I explored the use of different shade levels in the coffee plantations to regulate the microclimate and developed a new simple BN shade model to infer the required shade level considering local air temperatures [Chapter 5]. The model includes suitability functions from ALECA that allows the shade model to estimate the temperature suitability for coffee under shaded and unshaded conditions. The model was validated and used on coffee areas in Nicaragua under current conditions and a scenario of climate change [RCP 4.5]. The results showed that even at higher altitudes an increment in shading levels will be required to alleviate the impacts of climate change and that at lower altitudes the cooling effect of shade trees may not be enough in some areas to fully compensate for the warming conditions. The expected changes in the shade levels should be considered in future agroforestry planning processes in addition to farmers' objectives. Overall, the analysis showed that shading improves the local conditions in favor of the coffee plant, and should, therefore, be considered as an adaptation measure in further studies that address climate change impacts on coffee systems.

3) Potential tradeoffs and synergies between productivity, adaptation, and mitigation [PAM] objectives in coffee agroforestry systems. I developed a new farming typology and model to enhance the analysis of tradeoffs and synergies between productivity, adaptation and mitigation objectives [Chapter 6 and 7]. The new PAM-typologies classify the different existing coffee agroforestry systems based on several key features influencing PAM objectives. The farm type dominated by woody trees has many synergies between PAM-objectives if shade levels are medium to high, but if shade levels are low, synergies are more abundant in the type dominated by musaceas.

The BN model based on a farm typology enhances the understanding of the synergies and tradeoffs found in different systems when considering multiple objectives. It can be used to explicitly display the differences and similarities and gradual changes between typologies, and also provides the option to evaluate changes in farmers' objectives and farming practices. My application of the model showed that under future climate conditions, even when using optimal shade levels as an adaptation measure against higher temperatures and farm management that maximizes production, a reduction in income from coffee cultivation is inevitable in Nicaragua. However, the higher tree densities and higher carbon contents of these coffee agroforestry systems at least provide more food and shelter to wild species and improve conservation efforts.

8.1. Outlook and concluding remarks

The studies presented in this thesis represent a framework to assess the impacts of climate change on coffee systems in Central America and to evaluate possible management alternatives considering multiple objectives. A similar modeling approach can be used by researchers and practitioners to address other threats to coffee production or to evaluate other agricultural activities.

The single models described in the studies can also be used to explore other problems or subjects. The land suitability model, for example, can be used to evaluate a single farm or to identify new areas with a high potential for coffee cultivation. The shade model could be integrated into an agroforestry carbon model to explore the possible implications of changes in tree species composition and density in coffee plantations on the below- and aboveground carbon stocks, which would be particularly useful to conduct carbon content estimations under uncertainty. The same strategy used to create the PAM-typologies and to explore the potential synergies and tradeoff between PAM-objectives can be used to explore others objectives or add new ones to the existing ones, e.g., tree species richness as a proxy for conservation objectives.

This thesis provides not only new modeling tools for the agroforestry community, but also new data that enhances the scientific knowledge base in the area of coffee production under climate change in Central America. The changes in land suitability between current and future climates provide an estimation about the magnitude of change that is to be expected and also enable stakeholders to compare the future potential of different coffee areas in the region. Furthermore, the study on shade levels and the corresponding effect on air temperature suitability offers a first assessment of the adaptation-by-cooling potential of agroforestry systems, and the new farming strategy typologies enable users to easily assess the synergies and tradeoffs between productivity, adaptation and mitigation objectives in coffee agroforestry systems.

Given the current efforts to select and breed new coffee varieties, an update of ALECA incorporating the different responses of different coffee varieties to the climate, soil, and landform components of the model may become necessary, as well as interactions between the three components. The shade model could be further improved by adding new variables and updating the model with additional data from different shade systems to better capture the differences in structure and composition of different coffee plantations.

Finally, the results of my thesis show that coffee farmers in Central America need support to increase their resilience against negative impacts of climate change. Otherwise, the livelihoods of millions of people involved in coffee production will be threatened, and land use changes from coffee agroforestry systems to pastoral or crop farming systems may threaten biodiversity and decrease environmental quality sharply in the region. Decision makers in the coffee sector, governments, and national and international organizations must step up and provide financial support, tools and guidelines for coffee producers. In order to ensure the success of such efforts and actions, strategic planning to identify the most suitable strategy for each farmer is necessary. This thesis provides new knowledge, data and tools to support this endeavor, and to ensure the continuity of coffee cultivation in Central America.

9. REFERENCES

Acock, M.C., Pachepsky, Y.A., 2000. Estimating missing weather data for agricultural simulations using group method of data handling. Journal of Applied meteorology 39, 1176–1184. https://doi.org/10.1175/1520-0450(2000)039<1176:EMWDFA>2.0.CO;2

Adams, J., 2010. Vegetation-climate interaction: how plants make the global environment, 2nd ed, Springer-Praxis books in environmental sciences. Springer ; In Association with Praxis, Berlin ; New York : Chichester, UK.

Aguilar, V., Staver, C., Milberg, P., 2003. Weed vegetation response to chemical and manual selective ground cover management in a shaded coffee plantation. Weed Research 43, 68–75. https://doi.org/10.1046/j.1365-3180.2003.00318.x

Aguilera, P.A., Fernández, A., Fernández, R., Rumí, R., Salmerón, A., 2011. Bayesian networks in environmental modelling. Environmental Modelling & Software 26, 1376–1388. https://doi.org/10.1016/j.envsoft.2011.06.004

Albertin, A., Nair, P.K.R., 2004. Farmers' Perspectives on the Role of Shade Trees in Coffee Production Systems: An Assessment from the Nicoya Peninsula, Costa Rica. Human Ecology 32, 443–463. https://doi.org/10.1023/B:HUEC.0000043515.84334.76

Alégre, C., 1959. Climates et caféiers d´Arabie. Agronomie Tropicale 14, 23–58.

Allan, J.D., Yuan, L.L., Black, P., Stockton, T., Davies, P.E., Magierowski, R.H., Read, S.M., 2012. Investigating the relationships between environmental stressors and stream condition using Bayesian belief networks. Freshwater Biology 57, 58–73. https://doi.org/10.1111/j.1365-2427.2011.02683.x

Altamirano, J.A., 2011. Estudio de Perfiles de Taza del café (Coffea arabica) cultivado en el municipio de Jinotega-Nicaragua. Ciclo cafetalero del 2007-2008 al 2009-2010. Conglomerado del Cafe Jinotega/AECI, Jinotega, Nicaragua.

Alves, E.P., Silva, M.L. da, Neto, O., De, S.N., Barrella, T.P., Santos, R.H.S., 2015. ECONOMIC ANALISYS OF A COFFEE-BANANA SYSTEM OF A FAMILY-BASED AGRICULTURE AT THE ATLANTIC FOREST ZONE, BRAZIL. Ciência e Agrotecnologia 39, 232–239. https://doi.org/10.1590/S1413-70542015000300004

Alves, M. de C., de Carvalho, L.G., Pozza, E.A., Sanches, L., Maia, J.C. de S., 2011. Ecological zoning of soybean rust, coffee rust and banana black sigatoka based on Brazilian climate changes. Procedia Environmental Sciences 6, 35–49. https://doi.org/10.1016/j.proenv.2011.05.005

ANACAFE, 2018. La sombra y el cafe [WWW Document]. ANACAFE. URL http://www.anacafe.org/glifos/index.php/La_sombra_y_el_cafe (accessed 5.23.18).

ANACAFE, 2006. Guía Técnica de Caficultura. ANACAFE, Guatemala, Guatemala.

Andradóttir, S., Bier, V.M., 2000. Applying Bayesian ideas in simulation. Simulation Practice and Theory 8, 253–280. https://doi.org/10.1016/S0928-4869(00)00025-2

Arifin, J., 2001. Estimasi cadangan C pada berbagai sistem penggunaan lahan di Kecamatan Ngantang, Malang. Unibraw, Malang.

Atangana, A., Khasa, D., Chang, S., Degrande, A., 2014. Agroforestry and the Carbon Market in the Tropics, in: Tropical Agroforestry. Springer Netherlands, pp. 353–365.

Austin, M.P., 2002. Spatial prediction of species distribution: an interface between ecological theory and statistical modelling. Ecological Modelling 157, 101–118. https://doi.org/10.1016/S0304-3800(02)00205-3

Austin, M.P., 1980. Searching for a model for use in vegetation analysis. Vegetatio 42, 11–21. https://doi.org/10.1007/BF00048865

Avelino, J., Barboza, B., Araya, J.C., Fonseca, C., Davrieux, F., Guyot, B., Cilas, C., 2005. Effects of slope exposure, altitude and yield on coffee quality in two altitude terroirs of Costa Rica, Orosi and Santa María de Dota. Journal of the Science of Food and Agriculture 85, 1869–1876. https://doi.org/10.1002/jsfa.2188

Avelino, J., Cristancho, M., Georgiou, S., Imbach, P., Aguilar, L., Bornemann, G., Läderach, P., Anzueto, F., Hruska, A.J., Morales, C., 2015a. The coffee rust crises in Colombia and Central America (2008–2013): impacts, plausible causes and proposed solutions. Food Security 7, 303–321. https://doi.org/10.1007/s12571-015-0446-9

Avelino, J., Cristancho, M., Georgiou, S., Imbach, P., Aguilar, L., Bornemann, G., Läderach, P., Anzueto, F., Hruska, A.J., Morales, C., 2015b. The coffee rust crises in Colombia and Central America (2008–2013): impacts, plausible causes and proposed solutions. Food Sec. 7, 303–321. https://doi.org/10.1007/s12571-015-0446-9

Avelino, J., Perriot, J.J., Guyot, B., Decazy, F., Cilas, C., 2002. Identifying terroir coffees in Honduras, in: CIRADP-CP-CAFE (Ed.), Recherche et Caféiculture = Research and Coffee Growing, Plantations, Recherche, Développement. CIRAD-CP, Montpellier, France, pp. 6–16.

Babin, N., 2015. The Coffee Crisis, Fair Trade, and Agroecological Transformation: Impacts on Land-Use Change in Costa Rica. Agroecology and Sustainable Food Systems 39, 99–129. https://doi.org/10.1080/21683565.2014.960549

Bacon, C., 2005. Confronting the Coffee Crisis: Can Fair Trade, Organic, and Specialty Coffees Reduce Small-Scale Farmer Vulnerability in Northern Nicaragua? World Development 33, 497–511.

Badescu, V., 1993. Use of Willmott's index of agreement to the validation of meteorological models. The Meteorological Magazine 122, 282–286.

Barradas, V.L., Fanjul, L., 1986. Microclimatic chacterization of shaded and open-grown coffee (Coffea arabica L.) plantations in Mexico. Agricultural and Forest Meteorology 38, 101–112. https://doi.org/10.1016/0168-1923(86)90052-3

Barry, R.G., 2008. Mountain Weather and Climate., Third Edition. ed. Cambridge University Press, Leiden.

Barton, D.N., Kuikka, S., Varis, O., Uusitalo, L., Henriksen, H.J., Borsuk, M., de la Hera, A., Farmani, R., Johnson, S., Linnell, J.D., 2012. Bayesian networks in environmental and resource management. Integrated Environmental Assessment and Management 8, 418–429. https://doi.org/10.1002/ieam.1327

Beer, J., 1987. Advantages, disadvantages and desirable characteristics of shade trees for coffee, cacao and tea. Agroforestry Systems 5, 3–13. https://doi.org/10.1007/BF00046410

Beer, J., Muschler, R., Kass, D., Somarriba, E., 1998. Shade management in coffee and cacao plantations. Agroforestry Systems 38, 139–164.

Bellow, J.G., Nair, P.K.R., 2003. Comparing common methods for assessing understory light availability in shaded-perennial agroforestry systems. Agricultural and Forest Meteorology 15.

Bennett, N.D., Croke, B.F.W., Guariso, G., Guillaume, J.H.A., Hamilton, S.H., Jakeman, A.J., Marsili-Libelli, S., Newham, L.T.H., Norton, J.P., Perrin, C., Pierce, S.A., Robson, B., Seppelt, R., Voinov, A.A., Fath, B.D., Andreassian, V., 2013. Characterising performance of environmental models. Environmental Modelling & Software 40, 1–20. https://doi.org/10.1016/j.envsoft.2012.09.011

Bertrand, B., Alpizar, E., Lara, L., SantaCreo, R., Hidalgo, M., Quijano, J., Montagnon, C., Georget, F., Etienne, H., 2011. Performance of Coffea arabica F1 hybrids in agroforestry and full-sun cropping systems in comparison with American pure line cultivars. Euphytica 181, 147–158. https://doi.org/10.1007/s10681-011-0372-7

Bertrand, B., Rapidel, B. (Eds.), 1999. Desafíos de la caficultura en Centroamérica. IICA, PROMECAFE, San José, C. R.

Bertrand, B., Vaast, P., Alpizar, E., Etienne, H., Davrieux, F., Charmetant, P., 2006. Comparison of bean biochemical composition and beverage quality of Arabica hybrids involving Sudanese-Ethiopian origins with traditional varieties at various elevations in Central America. Tree Physiol 26, 1239–1248. https://doi.org/10.1093/treephys/26.9.1239

Bhattarai, S., Alvarez, S., Gary, C., Rossing, W., Tittonell, P., Rapidel, B., 2017. Combining farm typology and yield gap analysis to identify major variables limiting yields in the highland coffee systems of Llano Bonito, Costa Rica. Agriculture, Ecosystems & Environment 243, 132–142. https://doi.org/10.1016/j.agee.2017.04.016

Blackman, A., Alvalos-Sartorio, B., Chow, J., Aguilar, F., 2006. Tree Cover Loss in El Salvador's Shade Coffee Areas. Resources for the Future.

Blanco, R., Aguilar, A., 2015. Soil erosion and erosion thresholds in an agroforestry system of coffee (Coffea arabica) and mixed shade trees (Inga spp and Musa spp) in Northern Nicaragua. Agriculture, Ecosystems & Environment 210, 25–35. https://doi.org/10.1016/j.agee.2015.04.032

Blandford, T.R., Humes, K.S., Harshburger, B.J., Moore, B.C., Walden, V.P., Ye, H., 2008. Seasonal and Synoptic Variations in Near-Surface Air Temperature Lapse Rates in a Mountainous Basin. J. Appl. Meteor. Climatol. 47, 249–261. https://doi.org/10.1175/2007JAMC1565.1

Bonan, G.B., 2008. Ecological climatology: concepts and applications, 2nd ed. Cambridge University Press, Cambridge ; New York.

Bornemisza, E., Segura, A., 1999. Los suelos cafetaleros de América Central y su fertilización, in: Desafíos de la caficultura en Centroamérica. IICA, PROMECAFE, San José, C. R, pp. 97–137.

Boucher, S.R., Barham, B.L., Carter, M.R., 2005. The Impact of "Market-Friendly" Reforms on Credit and Land Markets in Honduras and Nicaragua. World Development 33, 107–128. https://doi.org/10.1016/j.worlddev.2004.09.004

Boudrot, A., Pico, J., Merle, I., Granados, E., Vílchez, S., Tixier, P., Filho, E. de M.V., Casanoves, F., Tapia, A., Allinne, C., Rice, R.A., Avelino, J., 2016. Shade Effects on the Dispersal of Airborne *Hemileia vastatrix* Uredospores. Phytopathology 106, 572–580. https://doi.org/10.1094/PHYTO-02-15-0058-R

Broegaard, R.B., 2010. Land Access and Titling in Nicaragua, in: Reader, T.S., Lundessor, C. (Eds.), The Politics of Possession. Wiley-Blackwell, pp. 142–161.

Bunn, C., Läderach, P., Pérez Jiménez, J.G., Montagnon, C., Schilling, T., 2015. Multiclass Classification of Agro-Ecological Zones for Arabica Coffee: An Improved Understanding of the Impacts of Climate Change. PLOS ONE 10, e0140490. https://doi.org/10.1371/journal.pone.0140490

Bunn, C., Läderach, P., Rivera, O.O., Kirschke, D., 2014. A bitter cup: climate change profile of global production of Arabica and Robusta coffee. Climatic Change 129, 89–101. https://doi.org/10.1007/s10584-014-1306-x

Cairns, M.A., Brown, S., Helmer, E.H., Baumgardner, G.A., 1997. Root biomass allocation in the world's upland forests. Oecologia 111, 1–11. https://doi.org/10.1007/s004420050201

Camargo, A., 1985. O clima e a cafeicultura no Brasil. Informe Agropecuario 11, 13–26.

Camargo, M.B.P. de, 2010. The impact of climatic variability and climate change on arabic coffee crop in Brazil. Bragantia 69, 239–247. https://dx.doi.org/10.1590/S0006-87052010000100030

Cannell, M.G.R., 1985. Physiology of the coffee crop, in: Coffee. Springer, pp. 108–134.

Cano, R., Sordo, C., Gutiérrez, J.M., 2004. Applications of Bayesian networks in meteorology, in: Advances in Bayesian Networks. Springer, Berlin, Germany, pp. 309–328.

Castellanos, E.J., Tucker, C., Eakin, H., Morales, H., Barrera, J.F., Díaz, R., 2013. Assessing the adaptation strategies of farmers facing multiple stressors: Lessons from the Coffee and Global Changes project in Mesoamerica. Environmental Science & Policy, Rethinking Integrated Assessments and Management Projects in the Americas 26, 19–28. https://doi.org/10.1016/j.envsci.2012.07.003

Castro-Tanzi, S., Dietsch, T., Urena, N., Vindas, L., Chandler, M., 2012. Analysis of management and site factors to improve the sustainability of smallholder coffee production in Tarrazú, Costa Rica. Agriculture, Ecosystems & Environment 155, 172–181. https://doi.org/10.1016/j.agee.2012.04.013

CATIE, MAGFOR, 2012. Elaboraciòn del mapa de cobertura cultivo de cafe de Nicaragua 2012 con base en imágenes de satelite landsat (Informe Final). Nicaragua.

CEPAL, 2002. Centroamérica: el impacto de la caída de los precios del café, Serie estudios y perspectivas. CEPAL, México, DF.

Cerda, R., Allinne, C., Gary, C., Tixier, P., Harvey, C.A., Krolczyk, L., Mathiot, C., Clément, E., Aubertot, J.-N., Avelino, J., 2017. Effects of shade, altitude and management on multiple ecosystem services in coffee agroecosystems. European Journal of Agronomy, Farming systems analysis and design for sustainable intensification: new methods and assessments 82, 308–319. https://doi.org/10.1016/j.eja.2016.09.019

Charlip, J.A., 2003. Cultivating coffee: the farmers of Carazo, Nicaragua, 1880-1930, Ohio University research in international studies. Latin America series. Ohio University Press, Athens.

Charlip, J.A., 1999. "So That Land Takes on Value": Coffee and Land in Carazo, Nicaragua. Latin American Perspectives 26, 92–105. http://www.jstor.org/stable/2634039

Chemura, A., Kutywayo, D., Chidoko, P., Mahoya, C., 2015. Bioclimatic modelling of current and projected climatic suitability of coffee (Coffea arabica) production in Zimbabwe. Reg Environ Change 1–13. https://doi.org/10.1007/s10113-015-0762-9

Chen, S.H., Pollino, C.A., 2012. Good practice in Bayesian network modelling. Environmental Modelling & Software 37, 134–145. https://doi.org/10.1016/j.envsoft.2012.03.012

Chinchilla, M., Mata, R., Alvarado, A., 2011. Andisoles, inceptisoles y entisoles de la subcuenca del río Pirrís, región de Los Santos, Talamanca, Costa Rica. Agronomía Costarricense 35, 83–107.

Cofiño, A., Cano, R., Sordo, C., Gutierrez, J., 2002. Bayesian Networks for Probabilistic Weather Prediction, in: van Harmelen, F. (Ed.), Proceedings of the 15th European Conference on Artificial Intelligence (ECAI 2002). Presented at the ECAI 2002, IOS Press, Lyon, France, pp. 675–700.

Conde, C., 2011. Coping with Climate Change Impacts on Coffee and Maize for Peasants in Mexico, in: Brauch, H.G., Oswald Spring, Ú., Mesjasz, C., Grin, J., Kameri-Mbote, P., Chourou, B., Dunay, P., Birkmann, J. (Eds.), Coping with Global Environmental Change, Disasters and Security, Hexagon Series on Human and Environmental Security and Peace. Springer Berlin Heidelberg, pp. 1067–1080.

Coudun, C., Gégout, J.-C., Piedallu, C., Rameau, J.-C., 2006. Soil nutritional factors improve models of plant species distribution: an illustration with Acer campestre (L.) in France. Journal of Biogeography 33, 1750–1763. https://doi.org/10.1111/j.1365-2699.2005.01443.x

DaMatta, F., Ronchi, C., Maestri, M., Barros, R.S., 2007. Ecophysiology of coffee growth and production. Brazilian Journal of Plant Physiology 19, 485–510. http://dx.doi.org/10.1590/S1677-04202007000400014

DaMatta, F.M., Ramalho, J.D.C., 2006. Impacts of drought and temperature stress on coffee physiology and production: a review. Brazilian Journal of Plant Physiology 18, 55–81. https://doi.org/10.1590/S1677-04202006000100006

De la Torre-Gea, G., Soto-Zarazúa, G.M., Guevara-González, R., Rico-García, E., 2011. Bayesian networks for defining relationships among climate factors. Int. J. Phys. Sci 6, 4412–4418. https://doi.org/10.5897/IJPS11.631

Defrenet, E., Roupsard, O., Van den Meersche, K., Charbonnier, F., Pastor Pérez-Molina, J., Khac, E., Prieto, I., Stokes, A., Roumet, C., Rapidel, B., de Melo Virginio Filho, E., Vargas, V.J., Robelo, D., Barquero, A., Jourdan, C., 2016. Root biomass, turnover and net primary productivity of a coffee agroforestry system in Costa Rica: effects of soil depth, shade trees, distance to row and coffee age. Ann Bot 118, 833–851. https://doi.org/10.1093/aob/mcw153

Descroix, F., Snoeck, J., 2004. Enviromental Factors Suitable for Coffee Cultivation, in: Wintgens, J.N. (Ed.), Coffee: Growing, Processing, Sustainable Production: A Guidebook for

Growers, Processors, Traders, and Researchers. Wiley-VCH Verlag GmbH, Weinheim, Germany, pp. 164–177.

Descroix, F., Wintgens, J.N., 2004. Establishing a Coffee Plantation, in: Wintgens, Jean Nicolas (Ed.), Coffee: Growing, Processing, Sustainable Production. Wiley-VCH Verlag GmbH, pp. 178–245.

D'haeze, D., Deckers, J., Raes, D., Phong, T.A., Loi, H.V., 2005. Environmental and socio-economic impacts of institutional reforms on the agricultural sector of Vietnam: Land suitability assessment for Robusta coffee in the Dak Gan region. Agriculture, Ecosystems & Environment 105, 59–76. https://doi.org/10.1016/j.agee.2004.05.009

Diaz, R., 2001. Situación y perspectivas de la caficultura en centro américa ante la crisis internacional de precios, Comercio y Medioambiente. CCAD-UN, Tegucigalpa, Honduras.

Eakin, H., Tucker, C.M., Castellanos, E., 2005. Market Shocks and Climate Variability: The Coffee Crisis in Mexico, Guatemala, and Honduras. Mountain Research and Development 25, 304–309. https://doi.org/10.1659/0276-4741(2005)025[0304:MSACVT]2.0.CO;2

Eakin, H., Tucker, C.M., Castellanos, E., Diaz-Porras, R., Barrera, J.F., Morales, H., 2014. Adaptation in a multi-stressor environment: perceptions and responses to climatic and economic risks by coffee growers in Mesoamerica. Environ Dev Sustain 16, 123–139. https://doi.org/10.1007/s10668-013-9466-9

Eccel, E., 2012. Estimating air humidity from temperature and precipitation measures for modelling applications. Meteorological Applications 19, 118–128. https://doi.org/10.1002/met.258

Ehrenbergerová, L., Cienciala, E., Kučera, A., Guy, L., Habrová, H., 2015. Carbon stock in agroforestry coffee plantations with different shade trees in Villa Rica, Peru. Agroforest Syst 1–13. https://doi.org/10.1007/s10457-015-9865-z

Eskelson, B.N.I., Anderson, P.D., Temesgen, H., 2013. Modeling Relative Humidity in Headwater Forests using Correlation with Air Temperature. Northwest Science 87, 40–58. https://doi.org/10.3955/046.087.0104

ESRI, 2008. How Aspect works [WWW Document]. URL http://webhelp.esri.com/arcgisdesktop/9.2/index.cfm?TopicName=How%20Aspect%20 works (accessed 9.23.15).

Fang, L., Qing-Cun, Z., Chao-Fan, L., 2009. A Bayesian Scheme for Probabilistic Multi-Model Ensemble Prediction of Summer Rainfall over the Yangtze River Valley. Atmospheric and Oceanic Science Letters 2, 314–319. https://doi.org/10.1080/16742834.2009.11446815

Fanjul, L., Arreola-Rodriguez, R., Mendez-Castrejon, M.P., 1985. Stomatal Responses to Environmental Variables in Shade and Sun Grown Coffee Plants in Mexico. Experimental Agriculture 21, 249–258. https://doi.org/10.1017/S0014479700012606

FAO (Ed.), 2001. Análisis de las consecuencias a mediano plazo del huracán Mitch sobre la seguridad alimentaria en América Central. FAO, Roma (Italy).

FAO, 1993. Guidelines for land-use planning, FAO development series. FAO, Rome.

FAO, 1976. A framework for land evaluation, Soils bulletin. Food and Agriculture Organization of the United Nations, Rome, Italy.

Fiala, A.C.S., Garman, S.L., Gray, A.N., 2006. Comparison of five canopy cover estimation techniques in the western Oregon Cascades. Forest Ecology and Management 232, 188–197. https://doi.org/10.1016/j.foreco.2006.05.069

Forestier, J., 1969. Culture du caféier Robusta en Afrique centrale: par J. Forestier,. Institut français du café et du cacao, Paris.

Franco, C.M., 1958. Influence of temperatures on growth of coffee plant, Bulletin. IBEC Research Institute, New York (EUA), New York, NY (EUA).

Frank, E., Eakin, H., López-Carr, D., 2011. Social identity, perception and motivation in adaptation to climate risk in the coffee sector of Chiapas, Mexico. Global Environmental Change 21, 66–76. https://doi.org/10.1016/j.gloenvcha.2010.11.001

Franklin, J., Miller, J.A., 2009. Mapping species distributions spatial inference and prediction. Cambridge University Press, Cambridge; New York.

Friedman, N., Geiger, D., Goldszmidt, M., 1997. Bayesian Network Classifiers. Machine Learning 29, 131–163. https://doi.org/10.1023/A:1007465528199

Fries, A., Rollenbeck, R., Nauß, T., Peters, T., Bendix, J., 2012. Near surface air humidity in a megadiverse Andean mountain ecosystem of southern Ecuador and its regionalization. Agricultural and Forest Meteorology 152, 17–30. https://doi.org/10.1016/j.agrformet.2011.08.004

Frolking, S., Qiu, J., Boles, S., Xiao, X., Liu, J., Zhuang, Y., Li, C., Qin, X., 2002. Combining remote sensing and ground census data to develop new maps of the distribution of rice agriculture in China. Global Biogeochemical Cycles 16, 38-1-38–10. https://doi.org/10.1029/2001GB001425

Fuentes-Franco, R., Coppola, E., Giorgi, F., Pavia, E.G., Diro, G.T., Graef, F., 2015. Inter-annual variability of precipitation over Southern Mexico and Central America and its relationship to sea surface temperature from a set of future projections from CMIP5 GCMs and RegCM4 CORDEX simulations. Climate Dynamics 45, 425–440. https://doi.org/10.1007/s00382-014-2258-6

Fuka, D.R., Walter, M.T., MacAlister, C., Degaetano, A.T., Steenhuis, T.S., Easton, Z.M., 2014. Using the Climate Forecast System Reanalysis as weather input data for watershed models: USING CFSR AS WEATHER INPUT DATA FOR WATERSHED MODELS. Hydrological Processes 28, 5613–5623. https://doi.org/10.1002/hyp.10073

Garedew, W., Hailu, B.T., Lemessa, F., Pellikka, P., Pinard, F., 2017. Coffee Shade Tree Management: An Adaptation Option for Climate Change Impact for Small Scale Coffee Growers in South-West Ethiopia, in: Leal Filho, W., Belay, S., Kalangu, J., Menas, W., Munishi, P., Musiyiwa, K. (Eds.), Climate Change Adaptation in Africa. Springer International Publishing, Cham, pp. 647–659. https://doi.org/10.1007/978-3-319-49520-0_40

Garming, H., Castellon, N., Rajala, S., Grote, U., Staver, C., 2013. Banana Value Chains in Central America - Options for Smallholders on Domestic and Regional Markets. Acta Horticulturae 331–338. https://doi.org/10.17660/ActaHortic.2013.986.35

Garnett, T., Appleby, M.C., Balmford, A., Bateman, I.J., Benton, T.G., Bloomer, P., Burlingame, B., Dawkins, M., Dolan, L., Fraser, D., Herrero, M., Hoffmann, I., Smith, P., Thornton, P.K., Toulmin, C., Vermeulen, S.J., Godfray, H.C.J., 2013. Sustainable Intensification in Agriculture: Premises and Policies. Science 341, 33–34. https://doi.org/10.1126/science.1234485

Gay, C., Estrada, F., Conde, C., Eakin, H., Villers, L., 2006. Potential Impacts of Climate Change on Agriculture: A Case of Study of Coffee Production in Veracruz, Mexico. Climatic Change 79, 259–288. https://doi.org/10.1007/s10584-006-9066-x

Ghahramani, Z., 1998. Learning dynamic Bayesian networks, in: Giles, C.L., Gori, M. (Eds.), Adaptive Processing of Sequences and Data Structures, Lecture Notes in Computer Science. Springer, Berlin, Heidelberg, pp. 168–197.

Giorgi, F., 2006. Climate change hot-spots. Geophys. Res. Lett. 33, L08707. https://doi.org/10.1029/2006GL025734

Godfray, H.C.J., Beddington, J.R., Crute, I.R., Haddad, L., Lawrence, D., Muir, J.F., Pretty, J., Robinson, S., Thomas, S.M., Toulmin, C., 2010. Food Security: The Challenge of Feeding 9 Billion People. Science 327, 812–818. https://doi.org/10.1126/science.1185383

Guillera-Arroita, G., Lahoz-Monfort, J.J., Elith, J., 2014. Maxent is not a presence–absence method: a comment on Thibaud et al. Methods Ecol Evol 5, 1192–1197. https://doi.org/10.1111/2041-210X.12252

Haarer, A.E., 1958. Modern Coffee Production. Leonard Hill Limited, London, England.

Häger, A., 2012. The effects of management and plant diversity on carbon storage in coffee agroforestry systems in Costa Rica. Agroforest Syst 86, 159–174. https://doi.org/10.1007/s10457-012-9545-1

Haggar, J., Barrios, M., Bolaños, M., Merlo, M., Moraga, P., Munguia, R., Ponce, A., Romero, S., Soto, G., Staver, C., de M. F. Virginio, E., 2011. Coffee agroecosystem performance under full sun, shade, conventional and organic management regimes in Central America. Agroforestry Systems 82, 285–301. https://doi.org/10.1007/s10457-011-9392-5

Haggar, J., Schepp, K., 2012. Coffee and Climate Change: Impacts and options for adaption in Brazil,Guatemala, Tanzania and Vietnam (No. 4), NRI Working Paper Series: NRI, University of Greenwich, UK.

Hairiah, K., Sitompul, S., Van Noordwijk, M., Palm, C., 2001. Methods for sampling carbon stocks above and below ground. ICRAF.

Harris, E., 2004. Building scientific capacity in developing countries. EMBO Rep 5, 7–11. https://doi.org/10.1038/sj.embor.7400058

Harrison, R.G., 2014. Humidity, in: Meteorological Measurements and Instrumentation, Advancing Weather and Climate Science Series. John Wiley & Sons, Ltd, Chichester, UK., pp. 103–122.

Harvey, C.A., Chacón, M., Donatti, C.I., Garen, E., Hannah, L., Andrade, A., Bede, L., Brown, D., Calle, A., Chará, J., Clement, C., Gray, E., Hoang, M.H., Minang, P., Rodríguez, A.M., Seeberg-Elverfeldt, C., Semroc, B., Shames, S., Smukler, S., Somarriba, E., Torquebiau, E., van Etten, J., Wollenberg, E., 2014. Climate-Smart Landscapes: Opportunities and Challenges for Integrating Adaptation and Mitigation in Tropical Agriculture. Conservation Letters 7, 77–90. https://doi.org/10.1111/conl.12066

Hauke, J., Kossowski, T., 2011. Comparison of Values of Pearson's and Spearman's Correlation Coefficients on the Same Sets of Data. Quaestiones Geographicae 30. https://doi.org/10.2478/v10117-011-0021-1

Hengl, T., de Jesus, J.M., MacMillan, R.A., Batjes, N.H., Heuvelink, G.B.M., Ribeiro, E., Samuel-Rosa, A., Kempen, B., Leenaars, J.G.B., Walsh, M.G., Gonzalez, M.R., 2014. SoilGrids1km — Global Soil Information Based on Automated Mapping. PLoS ONE 9, e105992. https://doi.org/10.1371/journal.pone.0105992

Hidalgo, H.G., Alfaro, E.J., Quesada-Montano, B., 2017. Observed (1970–1999) climate variability in Central America using a high-resolution meteorological dataset with implication to climate change studies. Climatic Change 141, 13–28. https://doi.org/10.1007/s10584-016-1786-y

Hidalgo, H.G., Amador, J.A., Alfaro, E.J., Quesada, B., 2013. Hydrological climate change projections for Central America. Journal of Hydrology 495, 94–112. https://doi.org/10.1016/j.jhydrol.2013.05.004

Hijmans, R.J., Cameron, S.E., Parra, J.L., Jones, P.G., Jarvis, A., 2005. Very high resolution interpolated climate surfaces for global land areas. International Journal of Climatology 25, 1965–1978. https://doi.org/10.1002/joc.1276

Hood, A., Cechet, B., Hossain, H., Sheffield, K., 2006. Options for Victorian agriculture in a "new" climate: Pilot study linking climate change and land suitability modelling. Environmental Modelling & Software, Integrative Modelling of Climatic, Terrestrial and Fluvial Systems, Integrative Modelling of Climatic, Terrestrial and Fluvial Systems 21, 1280–1289. https://doi.org/10.1016/j.envsoft.2005.04.022

Hopkins, L.D., 2014. Methods for Generating Land suitability Maps: A Comparative Evaluation, in: Ndubisi, F.O. (Ed.), The Ecological Design and Planning Reader. Island Press/Center for Resource Economics, pp. 348–367.

Ibargüengoytia, P.H., Garcıa, U.A., Herrera-Vega, J., Hernández-Leal, P., Morales, E.F., Sucar, L.E., Orihuela-Espina, F., Erro, L.E., 2013. On the Estimation of Missing Data in Incomplete Databases: Autoregressive Bayesian Networks, in: Ege, R., Koszalka, L. (Eds.), Eighth International Conference on Systems. Presented at the ICONS 2013, IARA, Seville, Spain, pp. 111–116.

ICAFE-CICAFE, 2011. Guía Técnica para el Cultivo del Café.

ICO, 2018. Prices paid to growers in exporting countries. International Coffee Organization.

ICO, 2015. Historical Data on the Global Coffee Trade [WWW Document]. URL http://www.ico.org/new_historical.asp?section=Statistics (accessed 9.11.15).

IICA, 2004. Cadena Agroindustrial del Cafe en Nicaragua. IICA, Managua, Nicaragua.

IICA, 2003. Cadena de Comercializacion del Café. Managua, Nicaragua.

INAFOR, 2009. Resultados del Inventario Nacional Forestal: Nicaragua 2007-2008. INAFOR, Managua, Nicaragua.

IPCC, 2014. ANNEX II: Glossary, in: March, K.., Planton, S., von Stechow, C. (Eds.), Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. IPCC, Geneva, Switzerland, pp. 117–130.

IPCC, Penman, J., IPPC National Greenhouse Gas Inventories Programme (Eds.), 2003. Good practice guidance for land use, land-use change and forestry /The Intergovernmental Panel on Climate Change. Ed. by Jim Penman. Hayama, Kanagawa.

Jakeman, A.J., Letcher, R.A., Norton, J.P., 2006. Ten iterative steps in development and evaluation of environmental models. Environmental Modelling & Software 21, 602–614. https://doi.org/10.1016/j.envsoft.2006.01.004

Jaramillo, A., Guzmán, M., 1984. Relación entre la temperatura y el crecimiento en Coffea arabica L. variedad Caturra. CENICAFE 35, 57–65.

Jensen, F.V., Nielsen, T., 2007a. Building Models, in: Bayesian Networks and Decision Graphs, Information Science and Statistics. Springer New York, pp. 51–108.

Jensen, F.V., Nielsen, T.D., 2007b. Bayesian networks and decision graphs., 2nd ed, Information science and statistics. Springer, New York.

Jha, S., Vandermeer, J.H., 2010. Impacts of coffee agroforestry management on tropical bee communities. Biological Conservation 143, 1423–1431. https://doi.org/10.1016/j.biocon.2010.03.017

Jungclaus, J.H., Keenlyside, N., Botzet, M., Haak, H., Luo, J.-J., Latif, M., Marotzke, J., Mikolajewicz, U., Roeckner, E., 2006. Ocean Circulation and Tropical Variability in the Coupled Model ECHAM5/MPI-OM. J. Climate 19, 3952–3972. https://doi.org/10.1175/JCLI3827.1

Kaimowitz, D., 1996. New Perspectives on Central American History, 1838-1945. Latin American Research Review 31, 201–210.

Kamusingize, D., Majaliwa, J.M., Komutunga, E., 2017. Allometric relationships and carbon content for biomass-carbon estimation of East African Highland Bananas (Musa spp. AAA-EAHB) cv. Kibuzi, Nakitembe, Enyeru and Nakinyika. Afr. J. Agric. Res. 9. https://doi.org/10.5897/AJAR2016.11960

Kandji, S.T., Verchot, L.V., Mackensen, J., Boye, A., Van Noordwijk, M., Tomich, T.P., Ong, C.K., Albrecht, A., Palm, C.A., Garrity, D.P., others, 2006. Opportunities for linking climate change adaptation and mitigation through agroforestry systems. World Agroforestry into the Future. Nairobi, Kenya.: World Agroforestry Centre-ICRAF 113–121.

Karmalkar, A.V., Bradley, R.S., Diaz, H.F., 2011. Climate change in Central America and Mexico: regional climate model validation and climate change projections. Climate Dynamics 37, 605–629. https://doi.org/10.1007/s00382-011-1099-9

Kevin Murphy, 2014. Software Packages for Graphical Models [WWW Document]. URL http://www.cs.ubc.ca/~murphyk/Software/bnsoft.html (accessed 7.26.17).

Khatri-Chhetri, A., Aggarwal, P.K., Joshi, P.K., Vyas, S., 2017. Farmers' prioritization of climate-smart agriculture (CSA) technologies. Agricultural Systems 151, 184–191. https://doi.org/10.1016/j.agsy.2016.10.005

Khatun, K., Imbach, P., Zamora, J.C., 2013. An assessment of climate change impacts on the tropical forests of Central America using the Holdridge Life Zone (HLZ) land classification system.

Knutti, R., Sedláček, J., 2012. Robustness and uncertainties in the new CMIP5 climate model projections. Nature Climate Change 3, 369–373. https://doi.org/10.1038/nclimate1716

Koller, D., 2009. Probabilistic graphical models: principles and techniques, Adaptive computation and machine learning. MIT Press, Cambridge, MA.

Korb, K.B., Nicholson, A., 2011. Bayesian artificial intelligence, 2nd ed. ed, Chapman & Hall/CRC computer science and data analysis series. CRC Press, Boca Raton, FL.

Kragt, M.E., Dumbrell, N.P., Blackmore, L., 2017. Motivations and barriers for Western Australian broad-acre farmers to adopt carbon farming. Environmental Science & Policy 73, 115–123. https://doi.org/10.1016/j.envsci.2017.04.009

Läderach, P., Lundy, M., Jarvis, A., Ramirez, J., Portilla, E.P., Schepp, K., Eitzinger, A., 2010. Predicted Impact of Climate Change on Coffee Supply Chains, in: Leal Filho, W. (Ed.), The Economic, Social and Political Elements of Climate Change, Climate Change Management. Springer Berlin Heidelberg, pp. 703–723.

Landuyt, D., Broekx, S., D’hondt, R., Engelen, G., Aertsens, J., Goethals, P.L.M., 2013. A review of Bayesian belief networks in ecosystem service modelling. Environmental Modelling & Software 46, 1–11. https://doi.org/10.1016/j.envsoft.2013.03.011

Lara-Estrada, L., 2005. Effects of the altitude, shade, production and fertilization on coffee quality (Coffea arabica L. var. Caturra) produced in agroforestry systems of coffee zone Northern Central of Nicaragua (M.Sc.). Spanish. Postgraduate School - CATIE, Turrialba, Costa Rica. http://hdl.handle.net/11554/4936.

Lara-Estrada, L., Rasche, L., Schneider, U.A., 2017. Modeling land suitability for Coffea arabica L. in Central America. Environmental Modelling & Software 95, 196–209. https://doi.org/10.1016/j.envsoft.2017.06.028

Lara-Estrada, L., Rasche, L., Sucar, L.E., Schneider, U.A., 2018. Inferring Missing Climate Data for Agricultural Planning Using Bayesian Networks. Land 7, 4. https://doi.org/10.3390/land7010004

Larcher, W., 1981. Effects of low temperature stress and frost injury on plant productivity, in: Physiological Processes Limiting Plant Productivity. Butterworth-Heinemann, pp. 253–269.

Lashermes, P., Bertrand, B., Etienne, H., 2009. Breeding Coffee (Coffea arabica) for Sustainable Production, in: Jain, S.M., Priyadarshan, P.M. (Eds.), Breeding Plantation Tree Crops: Tropical Species. Springer New York, pp. 525–543.

Lawrence, M.G., 2005. The Relationship between Relative Humidity and the Dewpoint Temperature in Moist Air: A Simple Conversion and Applications. Bulletin of the American Meteorological Society 86, 225–233. https://doi.org/10.1175/BAMS-86-2-225

Lee, J., 2017. Farmer participation in a climate-smart future: Evidence from the Kenya Agricultural Carbon Project. Land Use Policy 68, 72–79. https://doi.org/10.1016/j.landusepol.2017.07.020

Lin, B., 2008. Microclimate Effects on Flowering Success in Coffee Agroforestry Systems. American-Eurasian Journal of Agricultural & Enviroment 3, 148–152.

Lin, B.B., 2010. The role of agroforestry in reducing water loss through soil evaporation and crop transpiration in coffee agroecosystems. Agricultural and Forest Meteorology 150, 510–518. https://doi.org/10.1016/j.agrformet.2009.11.010

Lin, B.B., 2007. Agroforestry management as an adaptive strategy against potential microclimate extremes in coffee agriculture. Agricultural and Forest Meteorology 144, 85–94. https://doi.org/10.1016/j.agrformet.2006.12.009

Lin, B.-S., Lin, Y.-J., 2010. Cooling Effect of Shade Trees with Different Characteristics in a Subtropical Urban Park. HortScience 45, 83–86.

Linacre, E., Geerts, B., 2002. Estimating the annual mean screen temperature empirically. Theor Appl Climatol 71, 43–61. https://doi.org/10.1007/s704-002-8207-4

Little, R.J., Schenker, N., 1995. Missing data, in: Arminger, G., Clogg, C.C., Sobel, M.E. (Eds.), Handbook of Statistical Modeling for the Social and Behavioral Sciences. Springer, Boston, MA, USA, pp. 39–75.

Littleboy, M., Smith, D.M., Bryant, M.J., 1996. Simulation modelling to determine suitability of agricultural land. Ecological Modelling, Environmental and Ecological Models for Simulation and Management 86, 219–225. https://doi.org/10.1016/0304-3800(95)00055-0

Liu, D.L., Scott, B.J., 2001. Estimation of solar radiation in Australia from rainfall and temperature observations. Agricultural and Forest Meteorology 106, 41–59. https://doi.org/10.1016/S0168-1923(00)00173-8

López-Bravo, D.F., Virginio-Filho, E. de M., Avelino, J., 2012. Shade is conducive to coffee rust as compared to full sun exposure under standardized fruit load conditions. Crop Protection 38, 21–29. https://doi.org/10.1016/j.cropro.2012.03.011

Lopez-Rodriguez, G., Sotomayor-Ramírez, D., Amador, J., Schroder, E., 2015. Contribution of nitrogen from litter and soil mineralization to shade and sun coffee (Coffea arabica L.) agroecosystems. Tropical Ecology 56, 155-156. http://tropecol.com/volumes/toc/en/toc56–2.htm.

Luedeling, E., Smethurst, P.J., Baudron, F., Bayala, J., Huth, N.I., van Noordwijk, M., Ong, C.K., Mulia, R., Lusiana, B., Muthuri, C., Sinclair, F.L., 2016. Field-scale modeling of tree–crop interactions: Challenges and development needs. Agricultural Systems 142, 51–69. https://doi.org/10.1016/j.agsy.2015.11.005

MacVean, C., 1997. Coffee Growing: Sun or Shade? Science 275, 1401–1404. https://doi.org/10.1126/science.275.5306.1401d

Maestri, M., Barros, R.S., 1977. Coffee, in: Alvin, P., Kozlowski, T. (Eds.), Ecophysiology of Tropical Crops. Academic Press, Inc, New York, USA.

Magaña, V., Amador, J.A., Medina, S., 1999. The midsummer drought over Mexico and Central America. Journal of Climate 12, 1577–1588. http://dx.doi.org/10.1175/1520-0442(1999)012<1577:TMDOMA>2.0.CO;2

Mahjoub, M.A., Kalti, K., 2011. Software Comparison Dealing with Bayesian Networks, in: Liu, D., Zhang, H., Polycarpou, M., Alippi, C., He, H. (Eds.), Advances in Neural Networks – ISNN 2011, Lecture Notes in Computer Science. Springer Berlin Heidelberg, pp. 168–177.

Maloney, E.D., Camargo, S.J., Chang, E., Colle, B., Fu, R., Geil, K.L., Hu, Q., Jiang, X., Johnson, N., Karnauskas, K.B., Kinter, J., Kirtman, B., Kumar, S., Langenbrunner, B., Lombardo, K., Long, L.N., Mariotti, A., Meyerson, J.E., Mo, K.C., Neelin, J.D., Pan, Z., Seager, R., Serra, Y., Seth, A., Sheffield, J., Stroeve, J., Thibeault, J., Xie, S.-P., Wang, C., Wyman, B., Zhao, M., 2013. North American Climate in CMIP5 Experiments: Part III: Assessment of

Twenty-First-Century Projections*. J. Climate 27, 2230–2270. https://doi.org/10.1175/JCLI-D-13-00273.1

Marcot, B.G., 2012. Metrics for evaluating performance and uncertainty of Bayesian network models. Ecological Modelling 230, 50–62. https://doi.org/10.1016/j.ecolmodel.2012.01.013

Marcot, B.G., Steventon, J.D., Sutherland, G.D., McCann, R.K., 2006. Guidelines for developing and updating Bayesian belief networks applied to ecological modeling and conservation. Can. J. For. Res. 36, 3063–3074. https://doi.org/10.1139/x06-135

Mariño, Y.A., Pérez, M.-E., Gallardo, F., Trifilio, M., Cruz, M., Bayman, P., 2016. Sun vs. shade affects infestation, total population and sex ratio of the coffee berry borer (Hypothenemus hampei) in Puerto Rico. Agriculture, Ecosystems & Environment 222, 258–266. https://doi.org/10.1016/j.agee.2015.12.031

Matocha, J., Schroth, G., Hills, T., Hole, D., 2012. Integrating Climate Change Adaptation and Mitigation Through Agroforestry and Ecosystem Conservation, in: Nair, P.K.R., Garrity, D. (Eds.), Agroforestry - The Future of Global Land Use, Advances in Agroforestry. Springer Netherlands, pp. 105–126.

Matson, P.A., Parton, W.J., Power, A.G., Swift, M.J., 1997. Agricultural Intensification and Ecosystem Properties. Science 277, 504–509. https://doi.org/10.1126/science.277.5325.504

Mbow, C., Smith, P., Skole, D., Duguma, L., Bustamante, M., 2014a. Achieving mitigation and adaptation to climate change through sustainable agroforestry practices in Africa. Current Opinion in Environmental Sustainability 6, 8–14. https://doi.org/10.1016/j.cosust.2013.09.002

Mbow, C., Van Noordwijk, M., Luedeling, E., Neufeldt, H., Minang, P.A., Kowero, G., 2014b. Agroforestry solutions to address food security and climate change challenges in Africa. Current Opinion in Environmental Sustainability 6, 61–67. https://doi.org/10.1016/j.cosust.2013.10.014

McCann, R.K., Marcot, B.G., Ellis, R., 2006. Bayesian belief networks: applications in ecology and natural resource management. Canadian Journal of Forest Research 36, 3053–3062. https://doi.org/10.1139/x06-238

McConnell, D.J., Dillon, J.L., 1997. Farm management for Asia: a systems approach, FAO farm systems management series. FAO, Rome, Italy.

McNeely, J.A., 2004. Nature vs. nurture: managing relationships between forests, agroforestry and wild biodiversity. Agroforestry Systems 61–62, 155–165.

McRae, S.G. (Stuart G., Burnham, C.P. (Christopher P., 1981. Land evaluation, Monographs on soil survey. Clarendon Press ; Oxford University Press, Oxford : New York.

Medina, A., Harvey, C.A., Merlo, D.S., Vílchez, S., Hernández, B., 2007. Bat Diversity and Movement in an Agricultural Landscape in Matiguás, Nicaragua. Biotropica 39, 120–128. https://doi.org/10.1111/j.1744-7429.2006.00240.x

Meylan, L., Gary, C., Allinne, C., Ortiz, J., Jackson, L., Rapidel, B., 2017. Evaluating the effect of shade trees on provision of ecosystem services in intensively managed coffee plantations. Agriculture, Ecosystems & Environment 245, 32–42. https://doi.org/10.1016/j.agee.2017.05.005

Meylan, L., Merot, A., Gary, C., Rapidel, B., 2013. Combining a typology and a conceptual model of cropping system to explore the diversity of relationships between ecosystem services: The case of erosion control in coffee-based agroforestry systems in Costa Rica. Agricultural Systems 118, 52–64. https://doi.org/10.1016/j.agsy.2013.02.002

Mighty, M.A., 2015. Site suitability and the analytic hierarchy process: How GIS analysis can improve the competitive advantage of the Jamaican coffee industry. Applied Geography 58, 84–93. https://doi.org/10.1016/j.apgeog.2015.01.010

Miller, A.J., Gross, B.L., 2011. From forest to field: Perennial fruit crop domestication. Am. J. Bot. 98, 1389–1414. https://doi.org/10.3732/ajb.1000522

Miller, D., Robbins, M., Habiger, J., 2010. Examining the challenges of missing data analysis in phase three of the agricultural resource management survey, in: Proceedings of the Joint Statistical Meetings. Presented at the JSM 2010, American Statistical Association, Vancouver, Canada, pp. 816–829.

Moguel, P., Toledo, V.M., 1999. Biodiversity Conservation in Traditional Coffee Systems of Mexico. Conservation Biology 13, 11–21.

Molina, E., Melendez, G., 2002. Tabla de interpretación de análisis de suelos. Centro de Investigaciones Agronomicas, Universidad de Costa Rica, Costa Rica.

Montagnon, C., Marraccini, P., Bertrand, B., 2012. Breeding for coffee quality, in: Oberthür, T., Läderach, P., Cock, J.H. (Eds.), Specialty Coffee: Managing Quality. IPNI, Penang, Malaysia, pp. 89–117.

Morais, H., Caramori, P.H., Ribeiro, A.M. de A., Gomes, J.C., Koguishi, M.S., 2006. Microclimatic characterization and productivity of coffee plants grown under shade of pigeon pea in Southern Brazil. Pesquisa Agropecuária Brasileira 41, 763–770. https://doi.org/10.1590/S0100-204X2006000500007

Muschler, R., 2004. Shade Management and its Effect on Coffee Growth and Quality, in: Wintgens, J. (Ed.), Coffee: Groing, Processing, Sustainable Production.

Muschler, R.G., 2001. Shade improves coffee quality in a sub-optimal coffee-zone of Costa Rica. Agroforestry Systems 131–139. https://doi.org/10.1023/A:1010603320653

Nitlapan, 2012. Proyecto “Acceso a mercados de café diferenciados". Resultados de monitoreo y auditoría ambiental. (Project report). NITLAPAN-UCA, Managua, Nicaragua.

Nojavan A., F., Qian, S.S., Stow, C.A., 2017. Comparative analysis of discretization methods in Bayesian networks. Environmental Modelling & Software 87, 64–71. https://doi.org/10.1016/j.envsoft.2016.10.007

Norsys, 2018. Netica Help [WWW Document]. Netica Help. URL https://www.norsys.com/WebHelp/NETICA.htm (accessed 5.13.18).

Norsys, 2015. Netica Help [WWW Document]. URL http://www.norsys.com/WebHelp/NETICA.htm (accessed 9.15.15).

Nunes, M., Brumby, D., D Davies, 1973. Estudo comparativo do metabolismo fotossintético em folhas de cafeeiro, beterraba e cana-de-açúcar. Garcia de Orta, Série Estudos Agronómicos 1, 1–14.

Nzeyimana, I., Hartemink, A.E., Geissen, V., 2014. GIS-Based Multi-Criteria Analysis for Arabica Coffee Expansion in Rwanda. PLoS ONE 9, e107449. https://doi.org/10.1371/journal.pone.0107449

Okoth, P.F., Ng'ang'a, J.K., Kimani, P.K., 2007. Consequences of Field Management and Soil Erosion on the Sustainability of Large Scale Coffee Farming in Kiambu, in: Bationo, A., Waswa, B., Kihara, J., Kimetu, J. (Eds.), Advances in Integrated Soil Fertility Management in Sub-Saharan Africa: Challenges and Opportunities. Springer Netherlands, pp. 299–309.

Osman, K.T., 2013. Soils: Principles, Properties and Management. Springer Netherlands, Dordrecht.

Ovalle-Rivera, O., Läderach, P., Bunn, C., Obersteiner, M., Schroth, G., 2015. Projected Shifts in Coffea arabica Suitability among Major Global Producing Regions Due to Climate Change. PLoS ONE 10, e0124155. https://doi.org/10.1371/journal.pone.0124155

Panhuysen, S., Pierrot, J., 2018. Coffee barometer 2018. HIVOS, The Hague, The Netherlands.

Pearl, J., 1988. Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference, 1st ed. Morgan Kaufmann, San Francisco, USA.

Peixoto, J., Oort, A.H., 1996. The Climatology of Relative Humidity in the Atmosphere. J. Climate 9, 3443–3463. https://doi.org/10.1175/1520-0442(1996)009<3443:TCORHI>2.0.CO;2

Pérez, G., 2001. Los terremotos de 2001 y su impacto en la caficultura (No. 183), Boletín Económico y Social. FUSADES, Antiguo Cuscatlán, El Salvador.

Perfecto, I., Armbrecht, I., Philpott, S.M., Soto-Pinto, L., Dietsch, T.V., 2007. Shaded coffee and the stability of rainforest margins in northern Latin America, in: Stability of Tropical Rainforest Margins. Springer, pp. 225–261.

Perfecto, I., Rice, R.A., Greenberg, R., Voort, M.E. van der, 1996. Shade Coffee: A Disappearing Refuge for Biodiversity. BioScience 46, 598–608. https://doi.org/10.2307/1312989

Perfecto, I., Vandermeerb, J., Masa, A., Pinto, L.S., 2005. Biodiversity, yield, and shade coffee certification. Ecological Economics 54, 435–446.

Phillips, S.J., Anderson, R.P., Schapire, R.E., 2006. Maximum entropy modeling of species geographic distributions. Ecological Modelling 190, 231–259. https://doi.org/10.1016/j.ecolmodel.2005.03.026

Philpott, Stacy M, Arendt, W.J., Armbrecht, I., Bichier, P., Diestch, T.V., Gordon, C., Greenberg, R., Perfecto, I., Reynoso-santos, R., Soto-pinto, L., Tejeda-cruz, C., Williams-linera, G., Valenzuela, J., Zolotoff, J.M., 2008. Biodiversity Loss in Latin American Coffee Landscapes: Review of the Evidence on Ants, Birds, and Trees. Conservation Biology 22, 1093–1105. https://doi.org/10.1111/j.1523-1739.2008.01029.x

Philpott, Stacy M., Lin, B.B., Jha, S., Brines, S.J., 2008. A multi-scale assessment of hurricane impacts on agricultural landscapes based on land use and topographic features. Agriculture, Ecosystems & Environment 128, 12–20. https://doi.org/10.1016/j.agee.2008.04.016

Pineda, J.A., 2001. Establecimiento del cafetal, in: Manual de Caficultura. IHCAFE, Tegucigalpa, Honduras, p. 21.

Pollino, C.A., Henderson, C., 2010. Bayesian networks: A guide for their application in natural resource management and policy (Technical Report No. 14). LANDSCAPE LOGIC, Australia.

Pollino, C.A., Woodberry, O., Nicholson, A., Korb, K., Hart, B.T., 2007. Parameterisation and evaluation of a Bayesian network for use in an ecological risk assessment. Environmental Modelling & Software, Bayesian networks in water resource modelling and management 22, 1140–1152. https://doi.org/10.1016/j.envsoft.2006.03.006

Poppenborg, P., Koellner, T., 2014. A Bayesian network approach to model farmers' crop choice using socio-psychological measurements of expected benefits of ecosystem services. Environmental Modelling & Software 57, 227–234. https://doi.org/10.1016/j.envsoft.2014.03.006

Pretty, J., Toulmin, C., Williams, S., 2011. Sustainable intensification in African agriculture. International Journal of Agricultural Sustainability 9, 5–24. https://doi.org/10.3763/ijas.2010.0583

Primault, B., 1979. Transfer of Quantities of Air Masses, in: Agrometeorology. Springer, Berlin, Heidelberg, pp. 46–61. https://doi.org/10.1007/978-3-642-67288-0_10

PROMECAFE, 2018. El estado actual de la Rentabilidad del café en Centroamérica. CABI, Guatemala.

PROMECAFE, 2013. La crisis del cafe en Mesoamerica. Causas y respuestas apropiadas. IICA-PROMECAFE.

Pugh, T. a. M., Müller, C., Elliott, J., Deryng, D., Folberth, C., Olin, S., Schmid, E., Arneth, A., 2016. Climate analogues suggest limited potential for intensification of production on current croplands under climate change. Nature Communications 7, 12608. https://doi.org/10.1038/ncomms12608

Puyravaud, J.-P., 2003. Standardizing the calculation of the annual rate of deforestation. Forest Ecology and Management 177, 593–596. https://doi.org/10.1016/S0378-1127(02)00335-3

Ramírez, J., Jarvis, A., 2008. High Resolution Statistically Downscaled Future Climate Surfaces. International Center for Tropical Agriculture (CIAT); CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS), Cali, Colombia.

Ramírez, J.E., 2009. Hacia la caficultura sostenible. San José (Costa Rica).

Ramirez-Villegas, J., Jarvis, A., 2010. Downscaling global circulation model outputs: the delta method decision and policy analysis Working Paper No. 1. Policy Analysis 1, 1–18.

Ranatunga, K., Nation, E.R., Barratt, D.G., 2008. Review of soil water models and their applications in Australia. Environmental Modelling & Software 23, 1182–1206. https://doi.org/10.1016/j.envsoft.2008.02.003

Refsgaard, J.C., van der Sluijs, J.P., Højberg, A.L., Vanrolleghem, P.A., 2007. Uncertainty in the environmental modelling process – A framework and guidance. Environmental Modelling & Software 22, 1543–1556. https://doi.org/10.1016/j.envsoft.2007.02.004

Ribeiro, F.C., Borém, F.M., Giomo, G.S., De Lima, R.R., Malta, M.R., Figueiredo, L.P., 2011. Storage of green coffee in hermetic packaging injected with CO2. Journal of Stored Products Research 47, 341–348. https://doi.org/10.1016/j.jspr.2011.05.007

Richards, M.B., Méndez, V.E., 2014. Interactions between Carbon Sequestration and Shade Tree Diversity in a Smallholder Coffee Cooperative in El Salvador: Carbon Sequestration and Coffee Shade-Tree Species. Conservation Biology 28, 489–497. https://doi.org/10.1111/cobi.12181

Righi, C.A., Lunz, A.M.P., Bernardes, M.S., Pereira, C.R., Dourado-Neto, D., Favarin, J.L., 2008. Radiation Availability in Agroforestry System of Coffee and Rubber Trees, in: Jose, S., Gordon, A.M. (Eds.), Toward Agroforestry Design, Advances in Agroforestry. Springer Netherlands, pp. 249–266.

Rodríguez, D., Cure, J.R., Cotes, J.M., Gutierrez, A.P., Cantor, F., 2011. A coffee agroecosystem model: I. Growth and development of the coffee plant. Ecological Modelling 222, 3626–3639. https://doi.org/10.1016/j.ecolmodel.2011.08.003

Rojas, J., 2004. Green Coffee Storage, in: Wintgens, J.N. (Ed.), Coffee: Growing, Processing, Sustainable Production: A Guidebook for Growers, Processors, Traders, and Researchers. Wiley-VCH Verlag GmbH, Weinheim, Germany, pp. 733–750.

Rojas, O., 1989. Determinación del potencial agroecológico para el cultivo del café (Coffea arabica) en Costa Rica. Turrialba 39, 279–287.

Romps, D.M., 2014. An Analytical Model for Tropical Relative Humidity. J. Climate 27, 7432–7449. https://doi.org/10.1175/JCLI-D-14-00255.1

Roupsard, O., Gomez-Delgado, F., Rapidel, B., Le Maire, G., 2009. why is Agroforestry So Challenging for Modellers? How to Conciliate Complexity, Interctions, Accuracy and Upscaling. A proposed Strategy for Agroforestry Modelling., in: Rapidel, B., Roupsard, O., Navarro, M. (Eds.), Workshop Proceedings (25-29 February 2008), Technical Meetings No. 14. Presented at the Modelling Agroforestry Systems, CATIE, CATIE, Costa Rica, p. 336.

Rueda, X., Lambin, E.F., 2013. Linking Globalization to Local Land Uses: How Eco-Consumers and Gourmands are Changing the Colombian Coffee Landscapes. World Development 41, 286–301. https://doi.org/10.1016/j.worlddev.2012.05.018

Saha, S., Moorthi, S., Pan, H.-L., Wu, X., Wang, Jiande, Nadiga, S., Tripp, P., Kistler, R., Woollen, J., Behringer, D., Liu, H., Stokes, D., Grumbine, R., Gayno, G., Wang, Jun, Hou, Y.-T., Chuang, H.-Y., Juang, H.-M.H., Sela, J., Iredell, M., Treadon, R., Kleist, D., Van Delst, P., Keyser, D., Derber, J., Ek, M., Meng, J., Wei, H., Yang, R., Lord, S., Van Den Dool, H., Kumar, A., Wang, W., Long, C., Chelliah, M., Xue, Y., Huang, B., Schemm, J.-K., Ebisuzaki, W., Lin, R., Xie, P., Chen, M., Zhou, S., Higgins, W., Zou, C.-Z., Liu, Q., Chen, Y., Han, Y., Cucurull, L., Reynolds, R.W., Rutledge, G., Goldberg, M., 2010. The NCEP Climate Forecast System Reanalysis. Bulletin of the American Meteorological Society 91, 1015–1057. https://doi.org/10.1175/2010BAMS3001.1

Salazar, J.C.S., Bieng, M.A.N., Melgarejo, L.M., Rienzo, J.A.D., Casanoves, F., 2018. First typology of cacao (Theobroma cacao L.) systems in Colombian Amazonia, based on tree species richness, canopy structure and light availability. PLOS ONE 13, e0191003. https://doi.org/10.1371/journal.pone.0191003

Samper, M., 1999. Trayectoria y viabilidad de las Caficultoras Centroamericanas, in: Bertrand, B., Rapidel, B. (Eds.), Desafíos de La Caficultura En Centroamérica. IICA/PROMECAFE/CIRAD/IRD/CCCR, San José, Costa Rica, pp. 1–68.

Sarstedt, M., Mooi, E., 2014. Cluster Analysis, in: A Concise Guide to Market Research. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 273–324. https://doi.org/10.1007/978-3-642-53965-7_9

Schaller, N., Mahlstein, I., Cermak, J., Knutti, R., 2011. Analyzing precipitation projections: A comparison of different approaches to climate model evaluation. Journal of Geophysical Research 116. https://doi.org/10.1029/2010JD014963

Scherr, S.J., Shames, S., Friedman, R., 2012. From climate-smart agriculture to climate-smart landscapes. Agriculture & Food Security 1, 12. https://doi.org/10.1186/2048-7010-1-12

Schmitt-Harsh, M., Evans, T.P., Castellanos, E., Randolph, J.C., 2012. Carbon stocks in coffee agroforests and mixed dry tropical forests in the western highlands of Guatemala. Agroforest Syst 86, 141–157. https://doi.org/10.1007/s10457-012-9549-x

Schnabel, F., Filho, E. de M.V., Xu, S., Fisk, I.D., Roupsard, O., Haggar, J., 2017. Shade trees: a determinant to the relative success of organic versus conventional coffee production. Agroforest Syst 1–15. https://doi.org/10.1007/s10457-017-0100-y

Schneider, T., 2001. Analysis of incomplete climate data: Estimation of mean values and covariance matrices and imputation of missing values. Journal of Climate 14, 853–871. https://doi.org/10.1175/1520-0442(2001)014<0853:AOICDE>2.0.CO;2

Segura, M., Kanninen, M., Suárez, D., 2006. Allometric models for estimating aboveground biomass of shade trees and coffee bushes grown together. Agroforestry Systems 68, 143–150. https://doi.org/10.1007/s10457-006-9005-x

Shibl, R., Lawley, M., Debuse, J., 2013. Factors influencing decision support system acceptance. Decision Support Systems 54, 953–961. https://doi.org/10.1016/j.dss.2012.09.018

Siedenburg, J., Martin, A., McGuire, S., 2012. The power of “farmer friendly” financial incentives to deliver climate smart agriculture: a critical data gap. Journal of Integrative Environmental Sciences 9, 201–217. https://doi.org/10.1080/1943815X.2012.748304

Siles, P., Harmand, J.-M., Vaast, P., 2010. Effects of Inga densiflora on the microclimate of coffee (Coffea arabica L.) and overall biomass under optimal growing conditions in Costa Rica. Agroforestry Systems 78, 269–286. https://doi.org/10.1007/s10457-009-9241-y

Silva, S.A., Lima, J.S.S., Bottega, E.L., 2013. Yield mapping of arabic coffee and their relationship with plant nutritional status. Journal of soil science and plant nutrition 13, 556-564. http://ref.scielo.org/s5dspw.

Smith, P., Bustamante, M., Ahammad, H., Clark, H., Dong, H., Elsiddig, E.A., Haberl, H., Harper, R., House, J., Jafari, M., Masera, O., Mbow, C., Ravindranath, N.H., Rice, C.W., Abad, C.R., Romanovskaya, A., Sperling, F., Tubiello, F.N., Bolwig, S., 2014. Agriculture, Forestry and Other Land Use (AFOLU), in: Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, pp. 811–922.

Smith, T.M., Reynolds, R.W., Livezey, R.E., Stokes, D.C., 1996. Reconstruction of Historical Sea Surface Temperatures Using Empirical Orthogonal Functions. J. Climate 9, 1403–1420. https://doi.org/10.1175/1520-0442(1996)009<1403:ROHSST>2.0.CO;2

Somarriba, E., 2009. Planificación agroforestal de fincas (Material de enseñaza No. 49), Colección Módulos de Enseñanza Agroforestal No. 6. CATIE, Turrialba, Costa Rica.

Somarriba, E., 1992. Timber harvest, damage to crop plants and yield reduction in two Costa Rican coffee plantations with Cordia alliodora shade trees. Agroforest Syst 18, 69–82. https://doi.org/10.1007/BF00114817

Somarriba, E., Cerda, R., Orozco, L., Cifuentes, M., Dávila, H., Espin, T., Mavisoy, H., Ávila, G., Alvarado, E., Poveda, V., Astorga, C., Say, E., Deheuvels, O., 2013. Carbon stocks and cocoa yields in agroforestry systems of Central America. Agriculture, Ecosystems & Environment 173, 46–57. https://doi.org/10.1016/j.agee.2013.04.013

Somarriba, E., Harvey, C.A., Samper, M., Anthony, F., González, J., Staver, C., Rice, R.A., 2004. Biodiversity Conservation in Neotropical Coffee (Coffea arabica L.) Plantations, in: Schroth, G., da Fonseca, G., Harvey, C., Gascon, C., Vasconcelos, H., Izac, A. (Eds.), Agroforestry and Biodiversity Conservation in Tropical Landscapes. Island Press, Washington, DC, USA, pp. 198–226.

Souza, H.N. de, de Goede, R.G.M., Brussaard, L., Cardoso, I.M., Duarte, E.M.G., Fernandes, R.B.A., Gomes, L.C., Pulleman, M.M., 2012. Protective shade, tree diversity and soil properties in coffee agroforestry systems in the Atlantic Rainforest biome. Agriculture, Ecosystems & Environment 146, 179–196. https://doi.org/10.1016/j.agee.2011.11.007

Souza, H., Cardoso, I., Fernandes, J., Garcia, F., Bonfim, V., Santos, A., Carvalho, A., Mendonça, E., 2010. Selection of native trees for intercropping with coffee in the Atlantic Rainforest biome. Agroforestry Systems 80, 1–16. https://doi.org/10.1007/s10457-010-9340-9

Spiegelhalter, D.J., Dawid, A.P., Lauritzen, S.L., Cowell, R.G., 1993. Bayesian Analysis in Expert Systems. Statist. Sci. 8, 219–247. https://doi.org/10.1214/ss/1177010888

Staver, C., Bustamante, O., Siles, P., Aguilar, C., Quinde, K., Castellón, J., Somarriba, F., Tapia, A., Brenes, S., Deras, M., Matute, N., 2013. Intercropping Bananas with Coffee and Trees: Prototyping Agroecological Intensification by Farmers and Scientists. Acta Horticulturae 79–86. https://doi.org/10.17660/ActaHortic.2013.986.6

Streck, C., Burns, D., Guimaraes, L., 2012. Towards Policies for Climate Change Mitigation: Incentives and benefits for smallholder farmers (CCAFS Report No. 7). CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS), Copenhagen, Denmark.

Sucar, L.E., 2015a. Probabilistic graphical models: principles and applications, Advances in computer vision and pattern recognition. Springer, London Heidelberg New York Dordrecht.

Sucar, L.E., 2015b. Bayesian Networks: Learning, in: Probabilistic Graphical Models. Springer London, London, pp. 137–159. https://doi.org/10.1007/978-1-4471-6699-3_8

Sucar, L.E., 2015c. Bayesian Classifiers, in: Probabilistic Graphical Models. Springer London, London, pp. 41–62. https://doi.org/10.1007/978-1-4471-6699-3_4

Sys, C., Ranst, E. van, Debaveye, J., 1991. Land Evaluation. Part I. Principles in Land Evaluation and Crop Production Calculations, Agricultural Publications. Brussels, Bergium.

Taylor, M.A., Alfaro, E.J., 2005. Central America and the Caribbean, Climate of, in: Oliver, J. (Ed.), Encyclopedia of World Climatology, Encyclopedia of Earth Sciences Series. Springer, Dordrecht, Netherlands, pp. 183–189.

Teuber, R., 2009. Café de Marcala - Honduras' GI Approach to Achieving Reputation in the Coffee Market. Estey Centre Journal of International Law and Trade Policy 10, 131-148. http://purl.umn.edu/48798.

Thrall, P.H., Bever, J.D., Burdon, J.J., 2010. Evolutionary change in agriculture: the past, present and future. Evol Appl 3, 405–408. https://doi.org/10.1111/j.1752-4571.2010.00155.x

Tilman, D., Cassman, K.G., Matson, P.A., Naylor, R., Polasky, S., 2002. Agricultural sustainability and intensive production practices. Nature 418, 671–677. https://doi.org/10.1038/nature01014

Toledo, S.V., Barros, I., 1999. Influence of plant density and pruning system on the yield of coffee. Pesq.agropec.bras. 34, 1379–1384.

Tubiello, F.N., Salvatore, M., Rossi, S., Ferrara, A., Fitton, N., Smith, P., 2013. The FAOSTAT database of greenhouse gas emissions from agriculture. Environmental Research Letters 8, 015009. https://doi.org/10.1088/1748-9326/8/1/015009

Tucker, C.M., Eakin, H., Castellanos, E.J., 2010. Perceptions of risk and adaptation: Coffee producers, market shocks, and extreme weather in Central America and Mexico. Global Environmental Change 20, 23–32. https://doi.org/10.1016/j.gloenvcha.2009.07.006

Ukers, W., 1935. All about coffee, Second. ed. New York, USA.

USDA, 2015. Coffee Annual Report: Guatemala (GAIN Report No. 15003). Foreign Agricultural Service, USDA. http://www.fas.usda.gov/data/guatemala-coffee-annual-0.

Uusitalo, L., 2007. Advantages and challenges of Bayesian networks in environmental modelling. Ecological Modelling 203, 312–318. https://doi.org/10.1016/j.ecolmodel.2006.11.033

Vaast, P., Bertrand, B., Perriot, J.-J., Guyot, B., Génard, M., 2006. Fruit thinning and shade improve bean characteristics and beverage quality of coffee (Coffea arabica L.) under optimal conditions. Journal of the Science of Food and Agriculture 86, 197–204. https://doi.org/10.1002/jsfa.2338

Vaast, P., Cilas, C., Perriot, J.J., Davrieux, J.J., Guyot, B., Bolaños, M., 2004. Mapping of coffee quality in Nicaragua according to regions, ecological conditions and farm management, in: Proceedings of the 20th International Conference on Coffee Science. Presented at the 20th International Conference on Coffee Science, ASIC, Bangalore, India, pp. 842–850.

Vaast, P., Harmand, J.-M., Rapidel, B., Jagoret, P., Deheuvels, O., 2016. Coffee and Cocoa Production in Agroforestry—A Climate-Smart Agriculture Model, in: Climate Change and Agriculture Worldwide. Springer, Dordrecht, pp. 209–224. https://doi.org/10.1007/978-94-017-7462-8_16

Vaast, P., Jean-Jacques Perriot, Cilas, C., 2003. Proyecto Mejoramiento y Fortalecimiento en los Procesos de Certificación de Calidades y Comercialización del Café (Reporte Final). CIRAD, Turrialba, Costa Rica.

Vaast, P., Kanten, R., Siles, P., Angrand, J., Aguilar, A., 2008. Biophysical Interactions Between Timber Trees and Arabica Coffee in Suboptimal Conditions of Central America, in: Jose, S., Gordon, A.M., Nair, P.K.R. (Eds.), Toward Agroforestry Design, Advances in Agroforestry. Springer Netherlands, pp. 133–146.

Vaast, P., Martínez, M., Boulay, A., Castillo, B.D., Harmand, J.-M., 2015. Diversifying Central American Coffee Agroforestry Systems via Revenue of Shade Trees, in: Ruf, F., Schroth, G. (Eds.), Economics and Ecology of Diversification. Springer Netherlands, pp. 271–281. https://doi.org/10.1007/978-94-017-7294-5_13

Valenzuela, H., 2016. Agroecology: A Global Paradigm to Challenge Mainstream Industrial Agriculture. Horticulturae 2, 2. https://doi.org/10.3390/horticulturae2010002

Van Noordwijk, M., Lusiana, B., 1998. WaNuLCAS, a model of water, nutrient and light capture in agroforestry systems. Agroforestry Systems 43, 217–242. https://doi.org/10.1023/A:1026417120254

van Oijen, M., Dauzat, J., Harmand, J.-M., Lawson, G., Vaast, P., 2010. Coffee agroforestry systems in Central America: II. Development of a simple process-based model and preliminary results. Agroforestry Systems 80, 361–378. https://doi.org/10.1007/s10457-010-9291-1

Vega, F.E., Rosenquist, E., Collins, W., 2003. Global project needed to tackle coffee crisis. Nature 425, 343–343. https://doi.org/10.1038/425343a

Vega, M., Somarriba, E., 2005. Planificación agroforestal de fincas cacaoteras orgánicas del Alto Beni, Bolivia. Agroforestería en las Américas 43–44.

Velázquez, A., Mas, J.F., Gallegos, J.R.D., Saucedo, R.M., Alcántara, P.C., Castro, R., Fernández, T., Bocco, G., Ezcurra, E., Palacio, J.L., 2002. Patrones y tasas de cambio de uso del suelo en México. Gaceta Ecológica.

Verchot, L., 2005. Opportunities for linking adaptation and mitigation in agroforestry systems, in: Robledo, C. (Ed.), Tropical Forests and Adaptation to Climate Change: In Search of Synergies. Center for International Forestry Research CIFOR, Sindang Barang, pp. 103–121.

Verchot, L., Van Noordwijk, M., Kandji, S., Tomich, T., Ong, C., Albrecht, A., Mackensen, J., Bantilan, C., Anupama, K., Palm, C., 2007. Climate change: linking adaptation and mitigation through agroforestry. Mitigation and Adaptation Strategies for Global Change 12, 901–918. https://doi.org/10.1007/s11027-007-9105-6

Verheye, W., 2002. Management of Agricultural Land: Chemical and Fertility Aspects, in: Encyclopedia of Life Support Systems (EOLSS).

Verheye, W.H., 1987. Land Suitability Evaluation in Major Agro-ecological Zones and its Application in Land Use Planning and Nature Protection, in: Barth, H., L'Hermite, P. (Eds.), Scientific Basis for Soil Protection in the European Community. Springer Netherlands, pp. 377–388.

Vermeulen, S.J., Challinor, A.J., Thornton, P.K., Campbell, B.M., Eriyagama, N., Vervoort, J.M., Kinyangi, J., Jarvis, A., Laderach, P., Ramirez-Villegas, J., Nicklin, K.J., Hawkins, E., Smith, D.R., 2013. Addressing uncertainty in adaptation planning for agriculture. Proceedings of the National Academy of Sciences 110, 8357–8362. https://doi.org/10.1073/pnas.1219441110

Wagner, C.S., Brahmakulam, I., Jackson, B., Wong, A., Yoda, T., 2001. Science and technology collaboration: Building capability in developing countries? (No. MR-1357.0-WB). RAND, Pittsburgh, USA.

Wallis, J.A.N., 1963. Water use by irrigated Arabica coffee in Kenya. The Journal of Agricultural Science 60, 381–388. http://dx.doi.org/10.1017/S0021859600011977

Wang, N., Jassogne, L., van Asten, P.J.A., Mukasa, D., Wanyama, I., Kagezi, G., Giller, K.E., 2015. Evaluating coffee yield gaps and important biotic, abiotic, and management factors limiting coffee production in Uganda. European Journal of Agronomy 63, 1–11. https://doi.org/10.1016/j.eja.2014.11.003

WCR, 2018. Annual Report 2017: Creating the future of coffee.

Willmott, C.J., 1981. On the validation of models. Physical geography 2, 184–194. https://doi.org/10.1080/02723646.1981.10642213

Willson, K.C., 1985. Climate and Soil, in: Coffee. Botany, Biochemistry and Production of Beans and Beverage. New York, USA.

Woodward, F.I., Williams, B.G., 1987. Climate and plant distribution at global and local scales. Vegetatio 69, 189–197. https://doi.org/10.1007/BF00038700

World Bank., 2013. Weather data grids for agriculture risk management : the case of Honduras and Guatemala (No. 77780). The World Bank, Washington, DC, USA.

Yackulic, C.B., Chandler, R., Zipkin, E.F., Royle, J.A., Nichols, J.D., Campbell Grant, E.H., Veran, S., 2013. Presence-only modelling using MAXENT: when can we trust the inferences? Methods Ecol Evol 4, 236–243. https://doi.org/10.1111/2041-210x.12004

Young, A., 1987. Soil productivity, soil conservation and land evaluation. Agroforestry Systems 5, 277–291. https://doi.org/10.1007/BF00119126

Zeledon, E.B., Kelly, N.M., 2009. Understanding large-scale deforestation in southern Jinotega, Nicaragua from 1978 to 1999 through the examination of changes in land use and land cover. Journal of Environmental Management, Environmental and landscape change: Addressing an interdisciplinary agenda 90, 2866–2872. https://doi.org/10.1016/j.jenvman.2008.03.016

Zullo, J., Pinto, H.S., Assad, E.D., Ávila, A.M.H. de, 2011. Potential for growing Arabica coffee in the extreme south of Brazil in a warmer world. Climatic Change 109, 535–548. https://doi.org/10.1007/s10584-011-0058-0

ACKNOWLEDGMENT

My deep and sincere gratitude to my supervisors Prof. Dr. Uwe A. Schneider and Dr. Livia Rasche. Thank you for your time and comments on my research, and more importantly thanks for their respect and friendship. Certainly, I was lucky to have them.

Thank you to my colleagues in the Research Unit Sustainability and Global Change for sharing knowledge, experiences, and laughs.

Thanks to the Cluster of Excellence "Integrated Climate System Analysis and Prediction" (CliSAP, DFG-EXC177] and the School of Integrated Climate System Sciences [SICSS] at the Universität Hamburg for funding and support my research and give me the freedom to dig in my research interests.

Also many thanks to those who provided support in a particular part of my research, thanks to:

Chapter 2: Kompetenzzentrum Nachhaltige Universität (KNU] for funding a field trip to Nicaragua, Nitlapan-UCA, and FUNICA in Nicaragua for providing the data of Nitlapan [2012]. Dr. Bruno Rapidel for their comments over the early version of the model. Dr. Christophe Mongtanon, Dr. Enrique Succar, and two anonymous reviewers for their comments on the manuscript during the publishing process [published paper].

Chapter 4: Dr. Enrique Sucar for their comments, review, and contribution to the manuscript. Thank you to Dr. Eduardo Zorita for their comments to an early version of the manuscript. Thanks to the reviewers of the International Conference on Probabilistic Graphical Models [PGM 2016], and three anonymous reviewers for their comments on the manuscript during the publishing process [published paper].

Chapter 5: Dr. Jeremy Haggar and Andres Altamirano for sharing the dataset of Altamirano (2011), and Dr. Philippe Vaast for sharing the dataset of Vaast et al., (2003).

DECLARATION

I, Leonel Demócrito Lara Estrada, declare that this dissertation is only from my authorship. I designed the research framework, obtained the data, selected the method, developed the models and statistics, generated the results, and wrote the manuscripts of each chapter. Uwe Schneider and Livia Rasche supported the review of the results and edition of the manuscript. Uwe Schneider contributed to obtaining the modeling tool. Others contributions are indicated in Acknowledgement.

Published chapters:

Chapter 2:

Lara-Estrada, L., Rasche, L., Schneider, U.A., 2017. Modeling land suitability for Coffea arabica L. in Central America. Environmental Modelling & Software 95, 196–209. https://doi.org/10.1016/j.envsoft.2017.06.028

Chapter 4:

Lara-Estrada, L., Rasche, L., Sucar, L.E., Schneider, U.A., 2018. Inferring Missing Climate Data for Agricultural Planning Using Bayesian Networks. Land 7, 4. https://doi.org/10.3390/land7010004

An early version or part of my results were presented in international conferences:

Chapter 2:

Lara-Estrada L., Rasche L., Schneider U. 2015. Agroecological land evaluation for coffee production using Bayesian networks. In 12th Annual Bayesian Modeling Applications Workshop. The Netherlands.

Lara-Estrada L., Rasche L., Schneider U. 2016. Modeling the Agroecological Land Suitability for *Coffea arabica* L. in Central America. In EGU 2016. Vienna, Austria.

Chapter 3:

Lara-Estrada L., Rasche L., Schneider U. 2017. Un modelo probabilístico para explorar las alteraciones por el cambio climático en la aptitud climática de la tierra para la producción de café *Coffea arabica* L. In XXIII Simposio Latinoamericano de Caficultura. San Pedro Sula, Honduras.

Lara-Estrada L., Rasche L., Schneider U. 2016. A tool to explore the alterations of climate change on land suitability for *Coffea arabica* L. in Central America. In 5th EcoSummit. Montpellier, France.

Chapter 5:

Lara-Estrada L., Rasche L., Schneider U. 2019. A simple model to infer the required shade level in coffee plantations. In 4th World Congress on Agroforestry. Montpellier, France.

Chapter 6 & 7

Lara-Estrada L., Rasche L., Schneider U. 2016. Integrating ecosystem services to adapt and mitigate climate change in coffee agroforestry systems in Central America. In 5th EcoSummit. Montpellier, France.

Eidesstattliche Versicherung

Hiermit versichere ich, Leonel Demócrito Lara Estrada, an Eides statt, dass ich die vorliegende Dissertation mit dem Titel:

„Exploring the potential for adaptation and mitigation to climate change of coffee agroforestry systems in Central America"

selbstständig verfasst und keine anderen als die angegebenen Hilfsmittel – insbesondere keine im Quellenverzeichnis nicht benannten Internet-Quellen – benutzt habe. Alle Stellen, die wörtlich oder sinngemäß aus Veröffentlichungen entnommen wurden, sind als solche kenntlich gemacht. Ich versichere weiterhin, dass ich die Dissertation oder Teile davon vorher weder im In- noch im Ausland in einem anderen Prüfungsverfahren eingereicht habe und die eingereichte schriftliche Fassung der auf dem elektronischen Speichermedium entspricht.

Ort/Datum Unterschrift